CHAPTER ONE

AI in Investment Management

FIRMS WITH A HIGHER-LEVEL AWARENESS are not faring any better than those that lack imagination or alertness. When it comes to AI, firms seem to be split between denial and dysfunction. Those in denial view AI as a passing fad, an overly hyped phenomenon, a lustful yearning of large firms, a deviant path to shatter human relationships, and a phase whose efficacy parallels that of other digital technologies. Those in dysfunction are the fearless warriors who want to embrace anything that sounds like AI. They want AI at any cost—even if it means implementing AI without understanding what AI is, knowing how to plan and deploy AI, where and why to implement it, or how to maximize value from AI.

The ones in denial need no plan. The ones in dysfunction have none. Here are some examples of the above mindsets:

If you talk to investment management firms about AI as I do, you may hear something along these lines from the deniers: "I know our model works. We have been doing this for over 40 years. My clients know me. We meet regularly with clients. We have our methods, and we have perfected it as an art or a science—whatever you want to call it. I know how to find value. I know what my clients expect of me. I don't need no fancy technology." This narrative implies that the firm is confident that its existing business model is sustainable without any modification and augmentation from AI. For them, having AI is no better or worse than not having it.

The narratives of the dysfunctional firms are different. They display an aura of excitement and fascination about AI. In large legacy firms, the executives tend to use AI as the talking points to impress analysts, boards, and clients. Armies of AI suppliers and consultants occupy floors and floors of companies. Balloons, badges, and billboards of AI centers of excellence serve as power symbols to mark the supremacy and territorial invincibility of the newly architected transformation groups. Managers emerge as celebrities, award winners in supplier-sponsored conferences, and acquire newly found status and power. Futurists are brought in to paint rosy pictures of feel-good scenarios. Lofty and grandiose visions are crafted to elevate spirits and decorate resumes. Like *Titanic* setting sail for its epic but fateful journey, in exhilarating devotion, teams are structured, missions are developed, speeches are made, budgets are assigned, consultants are hired, suppliers are onboarded, and the transformation programs are launched. But after a year or so a deep feeling of anguish replaces the anticipated achievement. Project failures—whether evidenced by malfunctioning artifacts or by functioning projects with immaterial value contribution—become a discomforting reminder of complexity in producing results from AI. Transformation teams are disbanded—and then reconfigured. The reset button is pushed, and the "rinse, repeat" game starts again.

"Meet our youngest person on the team. She just joined us six months ago. She has developed this nice machine learning program that helps our people match their needs with various benefits," said the VP of human resources proudly. In the same firm, the head of marketing hired a consulting firm to implement chatbots. The board members were mesmerized to see a chatbot interacting with clients to answer trivial questions. The back-office accounting function went after a different consulting firm to implement what they thought was the best "AI solution"—something known as Robotic Process Automation (RPA). The regulatory department was not going to be left behind and got a different supplier for RPA and went with a different consulting firm. The head of the regulatory department tried to run an internal machine learning project but was unable to get results. Frustrated, she fired the team and restarted the project with another team. Quant departments—those that have solid experience in machine learning—observed all this chaos, laughed, and retreated to their silos. The walls of isolation went up. The strategic quarantining congealed. Each quant team had its own strategic outlook, its own AI team, its own way of doing things. Compliance got its own solution with an AI platform firm—but could not find the data to make the algorithm work. The audit department discovered that their firm has an AI lab set up in a foreign country—apparently a well-kept secret—and reached out to the team of researchers out there. The internal research team was thrilled to be discovered by the US-based functional areas within their own company and began working on the audit solutions. The head researcher remarked, "We do a lot of AI research, but no one in the firm knows about us. Everyone wants their own suppliers."

The above story of haphazard, unplanned, and chaotic accumulation of AI artifacts is not confined to a single legacy firm. This ailment of becoming theme-less art galleries of AI tools is inflicting nearly all large firms. Amid this chaotic adoption lies the real problem: for all this toil and drudgery, the legacy firms are losing their competitive advantage. A silent but ruthless competition is emerging from the fintech side. A fierce enemy is lurking in the shadows of innovation. The barbarians are not quite at the gate, but they are certainly amassing.

In smaller firms, things are not too different. Since the decision authority is limited to a handful of people, the dysfunction is more localized and centralized. One or two partners, mostly to satisfy their own inquisitiveness or ego, are demanding their IT shops to identify and implement AI solutions to help their business. When doing that, they either issue precise instructions to specify what they want, which tends to be some type of crude and obstinate automation of their existing business model, or they provide the IT shops free rein to explore what can be done. Since most IT shops in small firms are not equipped to handle AI solutions, they scramble to figure out how and where to start. Some reach out to consulting firms. Others try to find AI experts, professors, or AI platform companies. Some even take courses and attempt to develop their own AI solutions. But like their supersized competitors, smaller firms also lack the vision to architect a strategy for what one day will be viewed as the greatest transformation in human history.

Yet when non-quant leaders in investment management sit across data science people, they seem lost. In one of the largest surveys we conducted at the American Institute of AI, we found out what was on the minds of executives. They expressed to us the problems with the sudden rise of AI (paraphrased and expressed as collective sentiment to facilitate understanding):

1. How should I start my AI program? All these consulting firms are telling me different things. I cannot figure out how to start the enterprise program. My boss told me to start something with AI when she returned from a conference (or read an article or met with a consulting supplier).
2. What is cognitive transformation? Everyone I talk to gives different answers.

3. I hear all these terms, AI, RPA, deep learning, neural networks—what should I focus on?
4. How should I demonstrate value from AI?
5. How should I prioritize investment in AI? What comes first and what comes second and so on?
6. How should I develop skills?
7. What should be my business model? Is my business model changing?
8. What should I do about all the dangers of AI they keep warning me about?
9. How do I hire resources?
10. What is AI governance?

On one hand you have leaders who are having trouble understanding the revolution. On the other hand, you have AI, ML, and data science leaders who can drop unfathomable terms and mathematical concepts at lightning speed. So we have two sides in our companies—non-AI people who are feeling pressured to do something but do not know what and how, and the AI teams who are trying to make a contribution but fail to find support, budget allocation, and vision setting from the executive leadership teams.

This book is for everyone who is involved with the investment management world at any level. The reason for that is simple: this book is about transformation. It shows you how to transition from a twentieth-century classical digital era company to a modern AI firm. Transformation affects everyone and opens doors of opportunity for those who are ready to lead and embrace the revolution. This book is your guide to do just that.

If the goal of leading a business is to architect a sustainable competitive advantage, the only advantage that seems to have worked well in investment management firms is the one pursued by firms with well-organized quantamental operations (De Prado, 2018). These firms have created and operationalized a setup for machine learning–centric strategy development and execution, and that has led to creating profits for firms. But a firm is more than its quantamental strategy. Performance is not viewed as the sole criterion of success in investment management (Murphy, 2018). You need a business strategy beyond your quantitative investment strategies developed in your lab. You need a total transformation to function in the new era of AI.

This book answers all your above questions. It also creates a bridge between business and AI professionals and helps develop the strategic plan that both parties need. It gives control to business so that you can lead the transformation of your firm.

WHAT ABOUT AI SUPPLIERS?

In all this chaos, suppliers of AI are not helping. AI software suppliers can be divided into six types of firms:

- **Newly launched AI platform companies:** These firms claim to offer an AI platform. An AI platform, from their perspective, is a general-purpose solution that can be used to develop unlimited AI artifacts.
- **Tech giants platforms:** Large and established tech firms have launched their own versions of AI platforms.
- **RPA firms:** Robotic Process Automation is a rule-based software—which some argue is not AI—that has found significant adoption by many firms. It is simpler to understand for managers, and RPA vendors market it as the entry level solution to AI. Some even call it the gateway drug of AI. Some of the RPA players are blending their RPA (non-AI) offering with machine learning solutions to evolve as more integrated solutions.
- **Process automation firms:** The legacy business process reengineering firms are also repositioning their systems as AI solutions.
- **Other packaged or off-the-shelf:** Many firms offer packaged, or off-the-shelf, solutions that they claim to be AI solutions. Some of these suppliers have legitimate AI functionality; others have simply erased the B from their BI systems and replaced it with an A.
- **Function-specific AI firms:** These firms market AI solutions by functional areas such as marketing or human resources. Typically, their software contains some AI functionality. Many of these firms are venture-financed start-ups.

AI implementation firms are composed of the following:

- **Management consulting firms:** These are large management or strategy consulting firms.
- **Large systems integrators:** These firms are found in the echelons of Washington, DC government contracting space.
- **Tech firms:** Large tech firms such as Google and Amazon.
- **AI boutique firms:** Many AI-centered boutique firms are launched by AI professors and AI experts.
- **Data management firms:** Some of the basic data-centric support work is performed by data management firms.

Suppliers are equally confused about how to make sense of this technology. They tried to force-fit AI into compartments that they had built for digital transformations and which had worked reliably well for over four decades—but it all backfired. AI does not seem to fit the frames developed to implement ERP or CRM. Suppliers tried to explain to the clients that AI will transform their companies, but they could not explain how and why. They produced white papers and case studies but could not point to a single firm that had successfully transformed itself. Buried under decades of legacy, some even tried to repurpose the old molds of PowerPoints and business process reengineering era toolkits, but they did not impress the clients. They began recalibrating AI projects, only to discover that a great many were failing. After initial failure, some consulting firms had the audacity to advise the investment firms that they needed to go big and bet more, which essentially meant to have mega-sized *center of excellence* contracts with the consulting firms—but even for those who invested in those projects, the results did not improve much. Finally, the grandiose visions and promises of audacious transformations were tapered to on-the-ground realities. Suppliers of AI realized that the best way to sell to companies is to divide and conquer. Financial services firms were segmented into smaller pieces, and instead of selling visions of transformation, suppliers turned to selling small point solutions. Sales teams found entry paths leading into department heads, IT managers, and middle managers and began selling small point solution deals. The effect of such a sales strategy was catastrophic for clients. Investment firms turned into collectors of malfunctioning or substandard AI software, AI software proliferation ensued, and the process of death by the thousand papercuts started for many firms.

The strategy consulting firms are experiencing their own Darwin moment and are unsure how to function in the rapidly evolving AI-centered economy. The crisis unleashed by coronavirus has further shattered the AI management consulting industry. For the investment world, however, the pandemic has demonstrated the fragility of markets and made a strong case for the need for AI technology to help predict the emergent dynamics of the complex systems in which we operate in the modern era.

LISTENING WITHOUT JUDGING

ALI does not float like a butterfly or sting like a bee but most certainly was the only analyst in our institute who saw it coming. By mid-January of 2020, ALI was convinced that within the next 60 days, the US stock market would decline down to the 18,000 to 19,000 range. ALI became suspicious when a news report about some type of a viral outbreak in China caught ALI's attention. Many of us missed that little news segment as it stood too far away to make a dent in the rapidly shifting consciousness of the modern world. But not for ALI. ALI stands for Artificial Learning & Intelligence. ALI is an intelligent machine, and its story to predict the Covid-19-related crash of 2020 is as follows.

It was early January, and the world was focused on turmoil in the Middle East. A war was brewing, and geopolitical tensions were rising. Fear was in the air, but as we now know, for all the wrong reasons. ALI, who neither exhibits fears nor inhibits desires, was focused on something totally different. Ignoring all that was occupying our attention, it had picked up a trigger word related to a viral outbreak in China, and it was not ready to let go. Since viral outbreak could be the trigger words for ALI to identify a potentially serious risk, it was holding on to it as a dog holds on to a bone. Suddenly, the pattern-seeking mind of ALI went in hyper-stimulated mode when ALI began discovering words such as "SARS," "pandemic," "viral outbreak," "panic," and "human-to-human infection." Like hammers pounding on ALI's consciousness, these word combinations made it go in a panic mode of its own. By the third week of January of 2020, ALI began screaming for attention. It was ignoring the highly publicized impeachment proceedings, the looming threat of violence in the Middle East, the tragic death of a legendary basketball player, the Oscars, and the Superbowl. All of these events attracted tremendous attention and occupied human attention. But it was as if ALI knew that all these attention-grabbing events would take a backseat in consciousness when compared to what was coming. ALI kept insisting to pay attention to what would eventually come to be known as Covid-19.

As ALI passed on the findings, we knew some type of threat assessment would be needed. Let us examine three pieces of information that were published in articles in major newspapers in January:

1. Coronavirus disease is transmitting from human to human;
2. Coronavirus is killing people as people do not have immunity against it; and
3. Coronavirus has no vaccine.

Logic dictates that the above information was enough to project that in a deeply interconnected world this virus would spread throughout the globe, that it would be devastating for people, and that it would lead to a catastrophic negative financial impact. Despite the logical inference, the world ignored the threat. The stories that appeared in the newspapers were written as if it were a problem unfolding on a distant planet. The authors and journalists covered the story as if they were some impassionate observers studying the phenomenon taking place in a lab experiment and far removed from the reach of the virus. It was in China—a distant land. The language of the articles suggested that we were standing on some high ground, protected, and shielded, while watching Wuhan wash away in a flood of obscurity. Our lack of empathy was on full display. A sheer deprivation of insight was widely observable not only in the political circles of many countries but also in the financial markets. The Dow Jones Industrial was leisurely strolling in record territories, carefree and exuberant. Oblivious that a train wreck was heading in our direction, we casually responded, probably enjoying the bliss that ignorance offers with undeniable consistency. DJI remained energized. Not until the third week of February 2020 investors finally recognized something was off. And even then, it took a while before the state of denial was lifted. On March 23, 2020, DJI bottomed out at 18,591.

One of the commonly used models in epidemiology is known as the SIR model. SIR is used to study the spread of diseases. It is remarkably powerful and simple. It divides the world into three buckets. The first bucket is composed of potential patients—the population that can get infected. The second bucket is composed of those who get infected. The third of those who have recovered. Hence the name SIR, susceptible, infectious, and recovered. As we connected the outputs of ALI in the SIR model, we recognized that growth of the virus would be exponential. But beyond applying the SIR model for infectious disease, we decided to apply it to study the infection of news. Similar applications of SIR have been done to understand viral marketing. After all, news can be viewed as infection where uninformed (bucket 1) become informed (bucket 2) and reach a point where they take an action (bucket 3). The action could be anything, buying a product, voting for a candidate, or selling your stock. Estimating how and when a certain segment of the population gets ready to take a specific action is a valuable tool.

When we studied the spread of the news about coronavirus, we were able to estimate by what time markets would get infected enough to respond to the news. With historical responses for such events fed into another machine learning algorithm, we projected that the market would decline to 18,000 to 19,000 within two months. On March 23, 2020—almost 60 days from our projection—DJI declined to 18,591.

Anytime anyone claims that they have the crystal ball to see what is happening in the market, you have already made the biggest mistake in investment: hubris. Yes, you can be right once, but the market finds its own way. It always outsmarts you. Which obviously means that we probably got lucky and were not necessarily right. Thus, the lessons of the above story are not to brag that we got it right. The lessons are far more profound.

Lessons from ALI

The above story of ALI illustrates a few important ideas:

- Having an AI/ML-centric apparatus is critical to working out solutions to some of the most compelling investment problems. In our case, we were able to pick risk signals from a rather rudimentary apparatus.
- Model development is not a single pony show. Many models must be developed to solve a problem. The models form a nexus of interactive capabilities that are interdependent on each other and that reinforce the solution potential.
- These models work collaboratively to solve a problem.
- These models represent different types and levels of intelligence, and various types of intelligence and automation could be essential for broad automation.

As ALI's example shows, machine learning applications in finance are no longer isolated intelligent applications. They form a nexus of intelligence that drives value not just from the insights of a single application but also from the ecosystem of interactive and interdependent applications. This is a seismic change, and it has launched a new era in investment management. That era can be termed as the age of *industrial scale enterprise machine learning*. It will be helpful to first observe the four eras of intelligent automation.

THE FOUR STAGES OF AI IN INVESTMENTS

In modern and progressive investment firms, AI/ML has progressed through three stages of AI in the investment and asset management world, and with this book it will enter the fourth stage. These stages are not necessarily sequential from a temporal perspective. They are sequential in terms of a capability enhancement viewpoint. In other words, the eras are not defined from a time or chronological perspective, as some firms may still be operating in the less mature stage; instead they represent capability maturity. The following are the first three stages:

Stage 1: The Siloed Quant Era

In late 1990s, sitting at a Borders bookstore, I picked up two books on neural networks: (1) *Neural Networks for Financial Forecasting*; and (2) *Neural Networks in the Capital Markets* (Refenes, 1995; Gately, 1996). For that time, the books offered amazing insights into how to use neural networks in investment operations. I still have those books, and I keep them to remind me that decades before machine learning gained hyped status, financial services firms, and especially quant departments, were using it to create value.

Machine learning was the ultimate tool of the quants. Quants came from different backgrounds and expertise—for example, mathematics, physics, and econometrics. Their orientation and strategies deployed were different. Everyone wanted a shot at what they thought possible. Everyone had a dream and a method to achieve that dream. Everyone wanted to prove that they had cracked the code of market mysteries. Like gold miners or searchers from gold rush times, every quant had his or her own pans, pickaxes, and shovels. Since quants brought different methodologies and approaches to achieve alpha, firms viewed such separation as achieving diversification. Splitting into silos was encouraged because it was thought that the diversity in strategies would create a portfolio outcome where the average results would turn out to be favorable. The incentives were easier to manage since they could be easily aligned with the performance. For years, this style of research and investment continued. Even today, in many firms, this is still the dominant model. Despite the perceived benefit of diversification, such a partition has many undesirable effects:

1. Machine learning was viewed as the domain of quants and was not integrated in other functions in a firm;
2. Within the quant zone in a firm, capabilities stayed siloed and inaccessible by external parties;
3. Each quant turned into a small team of experts who all maintained their own view of the world, data, algorithms, and strategies;
4. Since various subprocesses of machine learning require specialized capabilities, the talent spread unevenly across the firm, provided low

opportunity to learn from each other, and it was impossible to streamline operations or build an assembly line of capabilities. As can be expected, this structure kept the costs high;

5. During major scandals or regulatory inquiries, as in the Great Recession, firms had to deal with the criticism that they were betting on both sides of the market or selling products while betting against your own products; and
6. No corporate level strategy of intelligent automation or artificial intelligence materialized.

Era 2: The Strategic Quant Era

Calls were made to streamline quant operations by eliminating silos. Experts suggested redesigning the investment operations and restructuring them along the themes of functional expertise in machine learning. They recognized that the costs associated with the first era setup were overwhelming. Also, as competitive forces shifted to AI-centric competition and strategy development, organizational realignment became necessary.

Machine learning itself is not a single process but is composed of several subprocesses. Designing quant departments along those lines of capabilities was a validation of the significant role played by machine learning in investment. As top experts—such as De Prado (De Prado, 2018)—called for change, they envisioned building departments that will acquire expertise in the functional aspects of machine learning such as data, data preprocessing, model development, model optimization, and deployment. This change is not only profound, but it also had many practical benefits:

- It streamlined machine learning operations and created economies of scope and scale.
- To make quant work more efficient, some firms began eliminating silos in the quant zone. Elimination of silos implied developing a shared mission and creating strategic coherence among the quant teams.
- Instead of viewing the internal silos as strategic diversification, these firms started viewing them as impediments to achieving a good strategy.
- It was recognized that a mix of good strategies can still be deployed while keeping costs low.

In some ways, adopting the second era meant that machine learning was not embraced as a technology or a capability but as a business model.

What De Prado was suggesting, in some ways, was to build the investment operation around machine learning. Machine learning was no longer just a tool to achieve alpha but a model of service value chain configured to drive and deliver incremental value. The operational realignment turned machine learning into an assembly line.

This change, while powerful, demanded (and will continue to demand) much-needed realignment in firms. It will require rediscovering and redeployment of talent, leadership awareness, and incentive redesign.

Stage 3: The Organizational Chaos Era

While the battles between the first two eras were being fought, machine learning silently rose to become widespread in other departments and functions in firms. It was no longer the exclusive domain of quants, and functional areas such as marketing, customer services management, regulatory and compliance, governance, and other departments and capability areas began embracing machine learning.

With the widespread adoption came the problem of unmanageable proliferation. I was involved in guiding one of the world's largest financial services firms on how to architect their machine learning and intelligent automation programs. That is where I was able to see firsthand the chaos unleashed by unplanned adoption of machine learning and intelligent automation. I realized that the firm had hundreds of projects going on all over the world. There was little to no coordination between the heads of departments leading these projects. Each department head had architected his or her own vision of automation—which was limited to their own political interests, capabilities, outlook, experience, and understanding of machine learning. Political fiefdoms developed, and departments began competing for AI talent. While all of that was going on, several consulting firms and suppliers jumped into the mix—each with its own angle, methodology, understanding, and interests. Given that no broad platform-centric capability set was available, each group, with the help from its own supplier and consulting firm, developed its customized expression of what needed to get done. Besides politics and self-interest (promotions, bonus, impressing higher executives, resume building), psychologies of various leaders also influenced their decisions. The ones with more aggressive personalities launched more aggressive programs. The more risk averse settled for developing some cute chatbots. In a meeting held with representation from across the firm, it was discovered that there were literally thousands of parallel, but uncoordinated, efforts going on in the company. Everyone had their own ideas of what AI and cognitive revolution is all about. The firm had become a weedy overgrown garden of AI artifacts. As you would have expected, the overall performance of the firm had not improved.

To appreciate the gravity of the situation, let us take a step back and evaluate the third era with the backdrop of the first two. As I mentioned before, shifting from the first era to the second era will be a monumental change. Realigning practices, rebuilding process streams, redefining incentive structures, and managing cultural change will take years and require organizational commitment, leadership vision, and execution excellence. It is not something that can be decoupled and reconfigured instantaneously. Now add to that companywide sporadic and unplanned adoption of machine learning point solutions, and you have a perfect storm. The third stage is a current reality for many firms—but it is a recipe for failure and a death spiral.

Now let us review the desired stage - Stage 4:

Stage 4: The Modern Investment Firm

The design of a modern investment management firm is based on the following insights:

- **Structural coherence:** No single capability is viewed as the sole determinant of success. A firm is viewed as a collection of capabilities that all transcend through various levels of intelligence.
- **Interdependence:** These capabilities interact with each other and through that interaction create interdependence where the entire system operates as a complex system.
- **External interaction:** Information flows into these capability areas from external systems, and the firm processes both internal and external information.
- **Performance maximizing:** The performance of each capability area is maximized, while ensuring that its interactions with other capability areas do not negatively affect the company goals.
- **Cohesive value building:** Each capability area is designed for performance, and the design focuses on two aspects: (1) automation and (2) intelligence. Automation, as the word implies, is work being performed by machines. Intelligence (I also use the term “intellectualization” interchangeably in this book) refers to the increase in human or machine knowledge to solve goal-oriented problems. Automation does not have to be intelligent. Intelligence does. The performance of automation is

measured by the ability of a machine to perform work efficiently. Efficiency refers to comparative performance of artifacts with humans and other machines. Intelligence, in contrast, is measured by the ability of a machine to successfully navigate through the uncertainty in accordance with the goals of the system.

- **Narrative empirical relationship:** Humans think in terms of narratives. We like to explain things in terms of cause and effect, relationships, correlations. Our search for truth sometimes lands us in areas that are dark and story-less. For example, with machine learning, we can observe that a certain trading strategy works, but we cannot explain why. Cohesive value building allows us to develop multilayered narratives supported by empirical research. Multilayered means that the narrative-empirical connection exists and functions at different levels in the firm. At the investment strategy level, we can explore dynamic narratives that emerge with empirical research. At the sales and marketing level we can articulate our investment philosophy, approach in terms of narratives, and support it with empirical research. At the firm level we can narrate our firm's strategy and support it with research. Machines do not deprive us of developing and understanding narratives. They simply give us answers with some homework assignments. Those of us who respect machines know that we must do our homework.

The fourth stage firm achieves interconnected excellence from the interaction of the network of various functional areas. However, both collectively (whole) and individually (parts), the system is managed using the scientific method.

THE CORE MODEL OF AIAI

Based on my work, the American Institute of Artificial Intelligence offers a model for transforming a company to the fourth stage. This model is based on the strategic factors discussed above, which serve as the underlying assumptions. For instance, the model assumes that management views the firm as a complex system composed of interconnected capabilities, where each capability has an individual role and a collective role. Secondly, the model proposes companywide adoption of the scientific method to run the company.

As shown in Figure 1.1, the vertical dimensions of the model are based on the value chain of a firm. The model shown here is for a general investment firm,

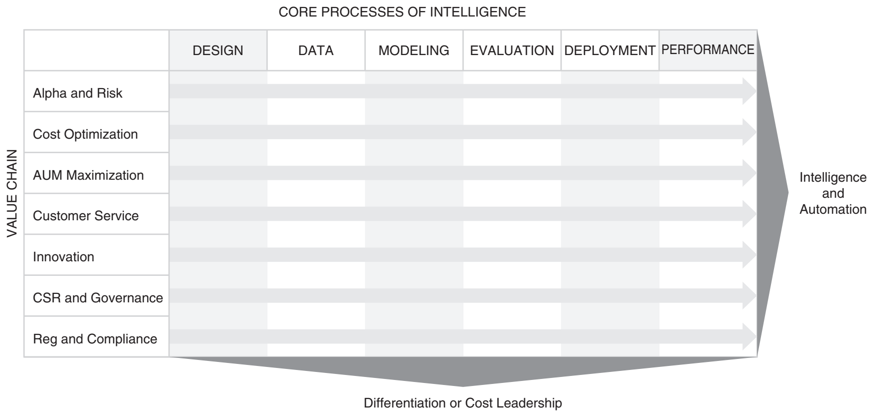

FIGURE 1.1 The AIAI Core Model

but it can be realigned and reconfigured in accordance with the unique nature of the firm (e.g., private equity or wealth management). Each value driver of the value chain has a specific goal. For example, the goal of alpha and risk is to generate alpha while managing risk in a firm. The goal of cost optimization is to decrease costs across the company. Note that the value drivers are not mapped as departments (e.g., operations, marketing, or sales). They are listed as capability areas. These capability areas can affect one or more departments. It is important to recognize that the functional departments–centric models—leftover from the twentieth-century bureaucratic organization—are no longer deemed necessary in the modern organization. I will explain that in Chapter 2. The capability areas are more consistent with the strategic goals of the entity, and it is assumed that each capability will tie in to one or more functional area organizations. Most importantly, the vertical dimension of strategic cohesiveness represents the strategy of the firm.

The horizontal dimension is composed of the scientific method, and it represents the operational excellence and execution potential of a firm. The scientific method is adopted to implement an industrial-scale enterprise machine learning approach for managing each function. The core processes of the scientific method include six competency areas of design, data, modeling, evaluation, deployment, and performance. Each one of those machine learning competency areas is independent of the vertical capability areas of the value chain. These competency areas are geared toward designing and developing machine learning solutions at an industrial scale.

When combined, the firm becomes a factory where AI artifacts are developed, deployed, nurtured, managed, and decommissioned at the end of the life cycle. Each of the artifacts plays a role in creating value for the business and is designed to be efficient and effective. The efficiency and effectiveness are determined in comparison to human performance or the performance of another machine and compared to the goals of the firm and the state of the competition and technical potential in the marketplace.

With both strategic excellence and operational excellence, firms are operated as research and science organizations—with every functional area transitioning to science-centric management. Thus, terms such as sales science, marketing science, human resources science, and supply chain science refer to the transformed organizations that are driven and led by data-centric planning and execution.

YOUR JOURNEY THROUGH THIS BOOK

Your journey through this book is divided into three parts. Part 1 starts you off in Chapter 2 with a focused coverage of investment management firm level strategy in the AI era. Chapters 3 through 8 focus on the horizontal competency areas of design, data, modeling, evaluation, deployment, and performance. Each of those chapters introduces the necessary capability areas and organizational structure to transform your firm to an AI-centric firm. Chapter 9 launches Part 2. Part 2 is function focused and from Chapters 10 through 17 covers customer experience science, marketing science, institutional investor science, investment science, supply chain science, and corporate social responsibility science. The addition of the word "science" to the traditional corporate organizations (for example, marketing or sales) is an acknowledgment that we are transforming our firms and business models in such a way that data science becomes the operational structure of the firm. Part 3 has three chapters: Chapter 18 is about AI project management, Chapter 19 covers governance and ethics issues, and Chapter 20 is the conclusion.

HOW TO READ AND APPLY THIS BOOK?

Chapters 2 to 8 show you how to restructure your firm for the AI era. They give you the new twenty-first-century structure to run your business in a scientific manner, understand that model, and then figure out how to set up your firm from a horizontal capability perspective.

Chapters 9 to 17 are about functional competencies. This is what we call departments in our twentieth-century terminology. We view them as functional capabilities embedded in the value chain of the firm. I strongly suggest that you read and understand the function-specific opportunities. Then build your functional capacities based on the applications introduced in the chapters—but their development and application should be done as a scientific process, introduced in Chapters 2 to 8.

A few notes about the book. While I was authoring this book, I was also writing a book on AI in auditing. Some chapters—especially the ones that introduce machine learning—will seem similar. As much as possible, I have kept the book simple and understandable for businesspeople. Finally, instead of limiting the book to a narrow definition of asset management, sometimes I use the broader category of investment management. If a certain section or topic coverage is not applicable to you, feel free to skip it—for example, if you are more interested in institutional, skip the retail section. Lastly, you will notice that I use both "I" and "we" throughout the book. When I use "we," I imply the American Institute of Artificial Intelligence.

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