EXPLANATION: A NEW ENTERPRISE DATA MONETIZATION CAPABILITY FOR AI

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RESEARCH SUMMARY

a summary of a research project with preliminary findings

INFORMATION TECHNOLOGIES

DATA, AI, AND ANALYTICS

DATA MONETIZATION

Artificial intelligence (AI) offers huge potential benefits for companies around the world. Companies that learn how to develop and deploy AI effectively will be positioned to maximize value creation in the emerging algorithmic economy, where algorithms will enable key business activities. Uptake of AI has been limited, however, and there are mounting associated concerns. This report explores what companies need to better understand about AI so they can make the most of this transformational phenomenon. The report describes distinct AI characteristics and their implications for enterprise data monetization capabilities, including a new requisite capability termed *explanation*.

CENTER FOR INFORMATION SYSTEMS RESEARCH (CISR)

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EXPLANATION: A NEW ENTERPRISE DATA MONETIZATION CAPABILITY FOR AI

Artificial Intelligence (AI) represents a set of technologies that produces exponential improvements in our ability to find patterns in data, make predictions, and recommend actions without explicit human instruction.[1]

AI investments have set records in recent years. In the US, investments in AI-related companies in 2019 reached $18.5 billion, representing a new high for money raised for startups.[2] AI has been promoted as the next general purpose technology, meaning it is expected to follow similar patterns of adoption as the steam engine and electricity, and eventually create considerable economic growth.[3] According to the McKinsey Global Institute, at a "global average level of adoption," AI could deliver 1.2 percent additional GDP growth annually.[4]

MIT CISR research suggests that AI also offers huge potential benefits for companies. AI projects can help companies generate value from data in myriad ways, ranging from improving with data to perform tasks better, cheaper, and faster; to wrapping data around products in the form of useful and engaging analytics features and experiences; to selling innovative informational solutions to the marketplace. In MIT CISR case studies, AI was used by Microsoft to streamline the enterprise sales process by predicting the likelihood of a sale to close;[5] by Cochlear to improve the sound experience of hearing implant patients, identifying sound contexts

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and automatically adjusting sound device settings;[6] and by BBVA to create information solutions for urban planning and disaster relief based on anonymized bank card records.[7]

Despite promising AI trends, forecasts, and reported examples, organizational adoption and deployment of AI remains low: only 20 percent of AI-aware companies are currently using AI in a core business process or at scale.[8] In this report, we explore reasons for lagging progress, and identify new capability requirements and effective managerial practices that can help business leaders manage for AI success.

About the Research

During phase one, two researchers convened an online discussion in Q1 2019 with the MIT Center for Information Systems Research Data Research Advisory Board. The board consisted of ninety-five executives representing sixty-seven large companies headquartered around the globe. Each executive was asked, What are the top three impediments to AI adoption in your company? Fifty-three data executives from fifty organizations answered the question (a 75 percent response rate). The two researchers analyzed the board answers and sorted them into distinct categories. Then, drawing on their professional experiences and the academic literature, the researchers identified whether categories were common to any data effort or unique to AI.

In phase two, an additional team member—who runs the AI practice for a global professional services company and who authored a book about AI— joined the two researchers. The new team member provided short write-ups of AI projects that have been conducted by her teams in recent years to illustrate ways in which AI obstacles were being overcome in practice.

ENTERPRISE DATA MONETIZATION CAPABILITIES AND OUTCOMES

MIT CISR research has found that companies must establish five enterprise capabilities to effectively monetize—generate economic returns from—their data.[9] The capabilities come into play regardless of whether data-based initiatives involve performance dashboards, enterprise reporting, business analytics, or artificial intelligence. The requisite enterprise capabilities include:

Data Asset: *Data that users can find, use, and trust*

A data asset capability produces in a digitized format high quality, understandable data that reflects reality. Key capability-building practices include master data management, metadata management, data integration, and data quality management. Data modelers and data source owners help the company build and manage its data asset capability.

Data Platform: *Technology that quickly, reliably, and cost-effectively serves up data*

A data platform capability securely and efficiently ingests, transforms, processes, and delivers data across and

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6 B. H. Wixom and R. Schüritz, "Creating Customer Value Using Analytics," MIT Sloan CISR Research Briefing, Vol. XVII, No. 11, November 2017, https://cisr.mit.edu/publication/2017_1101_WrappingAtCochlear_WixomSchuritz.

7 Elena Alfaro, Marco Bressan, Fabien Girardin, Juan Murillo, Ida Someh, and Barbara H. Wixom, "BBVA's Data Monetization Journey," MIS Quarterly Executive 18, Iss. 2, Article 4 (2019), pp. 117–128.

8 M. Chui, J. Manyika, N. Miremadi, Mehdi Henke, R. Chung, P. Nel, and S. Malhotra, "Notes from the AI Frontier Insights from Hundreds of Use Cases," McKinsey Global Institute (April 2018).

9 B. H. Wixom and K. Farrell, "Building Data Monetization Capabilities that Pay Off," MIT Sloan CISR Research Briefing, Vol. XIX, No. 11, November 2019, https://cisr.mit.edu/publication/2019_1101_DataMonCapsPersist_WixomFarrell; B. H. Wixom and L. Owens, "Digital Data Monetization Capabilities," MIT Sloan CISR Research Briefing, Vol. XIX, No. 4, April 2019, https://cisr.mit.edu/publication/2019_0401_Data-MonetizationCapabilities_WixomOwens.

beyond the enterprise. Key capability-building practices include use of APIs and leading-edge database tools and techniques (e.g., cloud computing, open source database software). Platform owners and data architects help the company build and manage its data platform capability.

Data Science: *Software, algorithms, and mathematical techniques that use data to detect what humans can't*

A data science capability extracts meaning and insights from data through the use of scientific tools and methods. Key capability-building practices include performance management, visualization, experimental design, programming, data scientist hiring and development, and data science training. Data scientists and citizen scientists help the company build and manage its data science capability.

Data Governance: *Norms and policies that ensure data-related activities are compliant and ethical*

A data governance capability ensures that the capture, management, and use of data is compliant with laws and regulations—and informed by organizational values and the values of ecosystem actors. Key capability-building practices include data lineage management, audits, data contract management, compliance and ethics training, and data privacy techniques. Data stewards and those in data security, privacy, risk, ethics, and compliance roles help the company build and manage its data governance capability.

Customer Understanding: *Knowledge about salient domain activities, influences, and outcomes*

A customer understanding capability senses core and latent needs and problems and responds in productive ways. Key capability-building practices include domain expert involvement, customer partnering, agile methods, cross-functional teams, and test-and-learn approaches and methodologies (e.g., A/B testing). Process, product, line-of-business, and customer channel owners each help the company build and manage its customer understanding capability.

Companies that establish high-quality enterprise data monetization capabilities can better deploy data projects that generate value by:

1. **Improving** core business processes using data—making money from doing things better, cheaper, and faster

2. **"Wrapping"** analytics around offerings—making money by distinguishing offerings with features and experiences

3. **Selling** information solutions—making money by deploying new information offerings

MIT CISR research found that top-performing companies in data monetization drive greater monetization outcomes by a factor of 2.5 as compared to bottom performers. They are able to achieve this because they have significantly stronger capabilities (see figure 1).[10]

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10 MIT CISR 2018 Data Monetization Survey (N=315). Firms split into distinct top (N=146) and bottom (N=105) performers on data monetization metrics (operational efficiencies created, increased prices/sales, direct revenues generated). Percentages show significant increases in capabilities from bottom to top performers, p<.0001.

Figure 1: Top Performers Have Stronger Data Monetization Capabilities than Bottom Performers
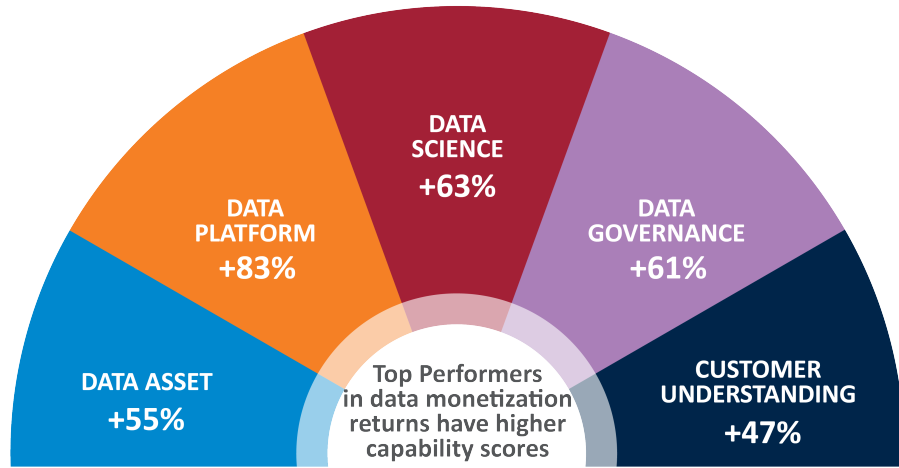
AI is an advanced form of data analytics that can self-learn and extract meaning from natural language.[11] AI can autonomously conduct tasks and engage with people; for example, customer service bots responding to online customer questions, and ride-hailing algorithms directing drivers as they pick up and drop off riders.

Based on our research, AI imposes additional data monetization capability requirements, and as such we anticipate that AI will widen the gap between data monetization top and bottom performers. The five data monetization capabilities are evolutionary—they build over time in predictable ways as companies progress from basic to more advanced practices (see figure 2).

Figure 2: Data Monetization Capabilities Are Evolutionary

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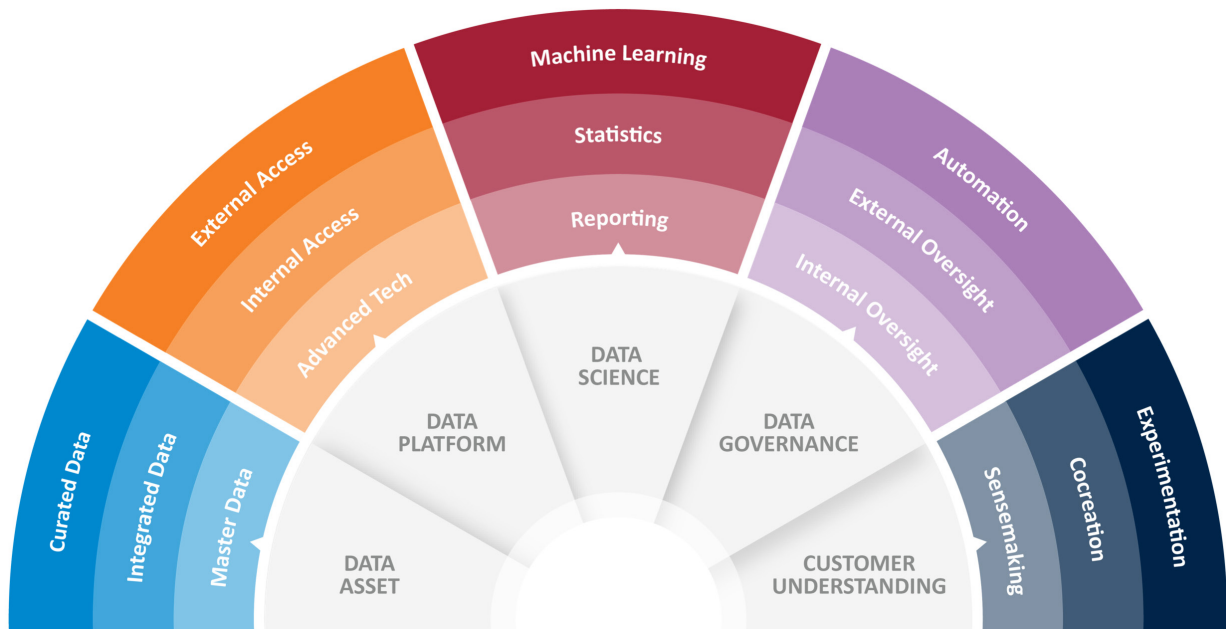
11 Brynjolfsson and Mitchell, "What can machine learning do? Workforce implications."

Figure 3 summarizes the additional data monetization capability requirements based on AI projects that we have studied. The table shows that AI projects tend to demand advanced data monetization capabilities across the board. As a result, before they can make meaningful inroads into AI, companies will need to build out data monetization capabilities that they have not yet developed. Figure 4 contains select executive comments[12] that illustrate the challenges that emerge when data monetization capabilities are inadequate for AI project needs.

Figure 3: AI Data Monetization Capability Requirements

	Data Asset	Data Platform	Data Science	Data Governance	Customer Understanding
AI projects need:	Curated data sets that are accurate, well understood, comprehensive, voluminous, and volatile	A scalable, on-demand platform that can regularly ingest, integrate, update, and process data and support external access	People, process, and technology that can build, train, deploy, and manage machine learning models over time	Oversight for decision risk, bias, and AI-enabled, automated action	Access to tacit and digitized information about business rules, rubrics, history, influences, changes, and exceptions, and experience in co-creation and experimentation

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12 Quotes and comments within this report were drawn from the Q1 2019 discussion with MIT CISR Data Board members. These statements have been anonymized to protect confidentiality.

Figure 4: AI Challenges Arising from Inadequate Data Monetization Capabilities

Data Asset Challenges

- *"**Availability of good clean data** is the most pressing issue right now. We are still in the infant stage of exploring what we might be able to do with our data and have some good ideas, but without the foundations there is limited ability to do a lot."*
- *"**Confusion regarding terminology and definitions** is fracturing our progress. A common lexicon can enable groups to work together more and make more progress."*
- *"**Lack of transaction data** on which to train."*
- *"Additional **data sets that can enhance** our internal transactional data with meaningful add-ons."*

Data Platform Challenges

- *"Need for **new architectures and technologies** not used in the traditional company."*
- *"**Scalable processing** power."*
- *"**Integration with legacy** systems that may be required to consume the AI algorithms by the business."*
- *"**Velocity of data ingestion** from multiple sources to enable consumption by data scientists."*

Data Science Challenges

- *"To get AI in use, data has to be assembled, **wrangled into an algorithm,** and the algorithm has to be put in a context where its results can matter."*
- *"**Skilled technical people** who understand our processes, data, and the AI technologies."*
- *"Lack of **skills and expertise in the business areas** to engage with, to identify what problems could be solved through AI capabilities."*
- *"The **culture of using data** to drive decisions, leading to ignorance on what data can solve for."*

Data Governance Challenges

- *"**Prioritization** across the organization (i.e., for AI to be effective, data efforts need to be very well aligned across the whole organization—not just in the analytics domain)."*
- *"Adoption of a **scalable framework, set of practices, and controls** to ensure that sensitive data, models, and work products are appropriately governed, protected, and shared, internally and with partners."*
- *"**Unclear policies** around consent, privacy, ethical use of data. Lack of clarity results in shutting down all data access to data scientists, and all requests are redirected through Legal/Risk/Compliance."*
- *"Putting the **right controls on exploratory platforms** so that experimentation can be done safely within regulatory and ethical bounds."*

Customer Understanding Challenges

- *"Not having a good **use case** for AI, which needs to be **driven from the business** rather than the Chief Data Analytics Office or Technology."*
- *"Means **to triage and scope** the business opportunity with confidence."*
- *"Value demonstration **at scale**."*
- *"There needs to be a way that is interactive, pleasing to the eye (UX Design) and 'dummied down' for general audiences to **interact with the AI and to modify** how it behaves on some basic parameters."*

A SIXTH ENTERPRISE DATA MONETIZATION CAPABILITY FOR AI: EXPLANATION

Our research suggests that in addition to the five enterprise data monetization capabilities we previously defined, AI projects require a sixth AI-specific capability that we have called *explanation*. The explanation capability ensures confidence in AI models that can be opaque, malleable, iffy, and unproven. The following sections describe these four distinct AI model challenges and their implications, and illustrate how companies currently build the explanation capability needed to fully exploit AI's potential.

AI is Opaque

"Fear of 'the black box.' We work in a very high-risk industry. It will be a long time before we leverage technologies that self-learn and limit or remove human interaction."

AI draws upon sophisticated computational mathematics and statistics that make it very hard for even some data scientists, never mind the layperson, to readily understand the model mechanics or output. Some AI models lack traceability, meaning there is no way to "follow the dots" from start to finish. For example, deep learning models make decisions by subtly adjusting up to hundreds of millions of numerical weights that interconnect nodes using intermediate abstractions that defy human reasoning. These models autonomously learn from example data and propagate their learning across an array of network layers. Even traceable AI models can be impossible for humans to follow along with, comprehend, or interpret. For example, textual classification models can have massive dimensionality and produce classification trees with thousands of words.[13]

The risk of AI opacity is that an untraceable or hard to trace model could be functioning incorrectly (e.g., violating regulatory requirements) or producing results that are wrong. Thus, AI teams must find ways to unravel the computations and mathematics at play and convey the "how" behind model results to those who need to consume and make use of the output.

The AI field increasingly is developing traceability techniques. For example, Local Interpretable Model-Agnostic Explanations (LIME) is a technique that varies inputs and observes the effect on outputs, including weights and accuracy scores to illuminate a model's mechanics. In another approach, AI teams triangulate model results by running competing models, or by comparing models with manual activities or incumbent processes. When opacity is simply not an option, some AI teams choose to trade model precision for traceability by using algorithms like simple decision trees or linear regression.

Challenge	Implication	Explanation Practice
AI is *opaque*	Lack of trace	Decision tracing

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13 David Martens and Foster Provost, "Explaining Data-Driven Document Classifications," MIS Quarterly 38, Iss. 1, pp. 73–99.

AI is Malleable

"[Our employees] have a hesitation in trusting the result, direction, or action the AI will take versus the good old-fashioned brain power of a traditional marketer, sales rep, data analyst, …"

AI works by consuming training data sets and using the data to construct decision-making rules that optimize specified outcomes or results. AI models are malleable in the sense that they will learn from whatever data they are given—whether good or bad—without inherent pushback or judgment.

The risk of AI's malleability is that a model could produce biased results. Biases can be technical in nature (such as from unbalanced data sets[14]), and bias can be functional in nature (such as from data sets incorporating prior discriminatory treatment). In either case, the AI model will produce results that are biased in the same way as was the data used to train it. Thus, AI teams must find ways to eliminate bias from model training activities.

The AI field has long stressed that companies should curate high-quality training data sets to avoid biased model results. AI teams use an array of statistical methods to check for technical bias. For example, they run statistical tests to evaluate underlying data distributions, identify missing data values, and assess field values and ranges. Functional bias is more difficult for AI teams to find and remediate. Typically, this happens through domain expert oversight in which experts in the domain review model output for face validity. In general, the teams have to make sure that training data sets include data that represents reality well and that includes rare events and exceptions, in addition to common occurrences.

Also, AI teams must manage AI models throughout their useful lives. After deployment, there is continued risk that bad data will be mistakenly introduced into the model feedback cycle—and that more timely or current patterns and exceptions will not be introduced. In either case, model results deteriorate over time, and even worse, begin misinforming humans or processes. For models that learn "on the fly," this degradation can happen quickly if bad data slips into the learning feedback loop. Thus, it's important that AI teams view model oversight as an ongoing organizational activity in which models are revalidated and possibly recreated at some regular frequency.

Challenge	Implication	Explanation Practice
AI is malleable	Technical and functional bias	Bias remediation

AI is Iffy

"AI by its very nature is imperfect."

We say AI is "iffy" because AI models produce results that are probabilistic. The models learn patterns and insights from training data and then apply those to a new specific instance with some degree (or lack) of confidence. Because there is some level of error in transferring learning from one situation to another situation, AI model results are not definitive. Rather, AI model results are tentative or conjectural and can't be immediately translated into IF-THEN rules.

AI requires careful application of its probabilistic results in real-world contexts. To do that, AI project teams have to deeply understand a domain's decision-making processes, standards, exceptions, and risks; realistically assess the precision and accuracy requirements for a decision situation; and acceptably translate an AI model's non-definitive output into meaningful messages that lead to the right action by humans and/or automated processes.

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14 If one variable is rare in a data set (e.g., a fraudulent transaction) the data set is said to be unbalanced with respect to that variable.

Otherwise, the risk is that AI insights may generate unexpected and unintended consequences, which could result in loss of life, health, money, or respect.

To get this right, AI teams combine quantitative assessment techniques like confusion matrices, accuracy percentages, and sensitivity analysis with qualitative model evaluation approaches like manual domain expert reviews and conservative decision thresholds that limit undesired errors. AI teams need to infuse into AI-enabled processes a heavy dose of human empathy and reasoning, particularly when it comes time to execute on AI-informed messages and decisions. Humans receiving messages may need to apply discretion, and automated decisions may need to be reversed.

Challenge	Implication	Explanation Practice
AI is iffy	Probabalistic outcomes	Boundary setting

AI is Unproven

"[Our executives] all hear about [AI], they want it, they think it is "cool" (direct quote from CCO). But when push comes to shove, they are hesitant to take away investment from traditional forms of P/L spend and invest in AI."

AI techniques have been maturing for decades, but only recently have synergistic advances in technology, data availability, and data science skills propelled AI into the mainstream. However, the market still lacks a broad selection of proven use cases, which means that leaders are uncertain regarding how and if their company can create meaningful returns from AI project investments. At the same time, there is significant risk involved in AI; when AI acts in undesired or wrong ways, companies face financial losses, reputational damage, or increased regulation and other constraints.

As a result, AI teams need to substantiate exactly how AI can be an attractive firm investment. They need to identify business pain or opportunity that AI solutions can address, and then show in a believable way how the company can assemble the right resources and capabilities to generate meaningful value. They need to demonstrate that decision making and processes can change to incorporate new AI insights into operational activities in sustained ways. Further, the teams' messages need to resonate with a wide array of internal stakeholders, such as technologists, end users, managers, executive champions, and funding committees—and external stakeholders like regulators and customers.

Challenge	Implication	Explanation Practice
AI is unproven	Lack of commitment	Multi-stakeholder value proposition formulation

Explanation

An enterprise data monetization capability, *explanation* specifically addresses AI's opaqueness, malleability, iffiness, and unproven nature (see figure 5). The explanation capability entails practices that help AI project teams establish trace, resolve bias, ensure compliance, and effectively deploy models to enable a company in realizing missions and appealing financial returns. In other words, an explanation capability helps AI teams establish and deploy fruitful AI projects—and build trust that AI will do the right thing in the right way at the right time.

Figure 5: Explanation

*Explanation: The ability to build confidence that AI will do the right thing
in the right way at the right time*

An explanation capability helps AI project teams develop models that are traceable, unbiased, compliant, safe to deploy, and lucrative. Key capability-building practices include decision tracing, bias remediation, boundary setting, and value formulation. AI experts, owners, and evangelists; data engineers; and AI UX designers and translators help the company build and manage its explanation capability.

Practices Enabled by Explanation	Implication	Explanation Outcome
Decision tracing	Clarifies how the AI model transforms inputs to outputs using mathematical calculations	Decision tracing
Bias remediation	Exposes how the AI model makes decisions about individual cases or a subset of cases and resolves unfairness, errors, flaws, and other problematic discrepancies	Model representativeness
Boundary setting	Elucidates how AI model outcomes need to be scoped, limited, or interpreted, including assumptions, conditions, contexts, and risks to consider when applying its outcomes	Model applicability
Value formulation	Articulates how AI model outcomes influence decisions, processes, and actions—and how associated changes will result in a combination of cost, risk, and value that produces a net gain for stakeholders	Model impact

IDEAL, FRUITFUL AI OPPORTUNITIES

Regardless of AI's unique demands, companies have good reason to be excited about AI opportunities: *AI models execute certain tasks better than humans and pre-existing processes and technology*. And the improvements can be exponentially better.

In the successful AI use cases that the MIT CISR research team has explored, AI worked faster, with less bias and error, and more comprehensively than the status quo. These results occurred because AI was selectively applied to projects where benefits far outweighed the costs of overcoming AI hurdles.

It's important to note that rarely do project teams choose AI when there are other data-based techniques available. In other words, whenever dashboards, simple regressions, or other common, straightforward data analytics approaches can solve a problem or meet a need, then AI options are best ignored.

However, there are myriad problems companies have been eager to solve for which no feasible solution has been found. These compelling, unmet business needs are the use cases that we suggest companies initially explore using AI. We have observed in our research quite a few examples of such use cases. A few illustrative examples include:

Needle in the haystack (or rare events):

The United States Securities and Exchange Commission (SEC)[15] wanted to identify hedge funds for further investigation using available performance data. Hedge fund performance data was reported to commercial data vendors for marketing purposes, but data was oftenincomplete. Thus, the SEC developed a proprietary model to analytically categorize and rank hedge funds as a part of a formal program called Aberrational Performance Inquiry. The agency used AI to identify outliers based on inconsistencies. Every month, the model estimated risk metrics for over 45,000 fund observations across eight data vendors. The model results were used to gather and verify information regarding particular funds or advisers, and the reports generated new leads for referral to Enforcement and the Office of Compliance Inspections and Examinations.

Dynamic, real-time response:

At AdJuggler,[16] AI was required to enable programmatic advertising. AdJuggler would run data through AI models in real time to execute the ad bidding process for every user who visited a website of an AdJuggler customer. The company created, managed, processed, delivered, and closed billions of ad spot sessions within milliseconds, and accomplished this within an ecosystem of twenty buy-side and sell-side data partners. Accuracy was critical. If an ad price was too high, advertisers would decline to bid on the ad space. If the price was too low, publishers would leave money on the table.

Complex array of influential attributes:

At PepsiCo,[17] one convenience store and gas (C&G) retailer wanted to maximize sales of its fountain drinks, some of which were PepsiCo's brands. The retailer did not know how many people actually purchased which drinks because their scan data only reflected the purchase of a cup, not its contents. First, PepsiCo Demand Accelerator (DX) associates combined PepsiCo's data about the number of gallons of syrup the retailer used with the retailer's data about its syrup purchases from other providers. Then, the DX team developed an ensemble of machine learning models that identified specific store and shopper attributes that influenced syrup usage.

Voluminous, unstructured data:

Spanish banking group BBVA[18] offered its Spain-based customers a personal finance management app. One of the app's tools used machine learning algorithms to sort customer transactions into common budgeting categories such as rent, food, and entertainment, and then displayed the customer's expenditures broken down as a simple chart. To create accurate categories from bank transaction data (such as free-text memo fields that customers may or may not fill in), the BBVA data science team transformed a variety of data sources from across the bank and ran them through a proprietary categorization engine. Daily, the engine processed millions of bank account and credit card transactions to classify them and enrich them with budget category labels.

Imagery or audio:

At Cochlear,[19] AI was used to offer a key mobile app feature for its behind-the-ear sound processor (part of an implantable hearing solution). The feature—called the SCAN Scene Classifier—applied algorithms to analyze a user's environment (e.g., crowded street corner, quiet room) and automatically adjust the sound processor's

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15 B. H. Wixom and J. W. Ross, "The US Securities and Exchange Commission: Working Smarter to Protect Investors and Ensure Efficient Markets," MIT Sloan CISR Working Paper No. 388, November 2012, https://cisr.mit.edu/publication/MIT_CISRwp388_SEC_WixomRoss.

16 B. H. Wixom and P. P. Tallon, "AdJuggler: Using Data Science to Serve the Right Ad at the Right Time," MIT Sloan CISR Working Paper No. 404, November 2015, https://cisr.mit.edu/publication/MIT_CISRwp404_AdJuggler_WixomTallon.

17 B. H. Wixom, "PepsiCo Unlocks Granular Growth Using a Data-driven Understanding of Shoppers," MIT Sloan CISR Working Paper No. 439, December 2019, https://cisr.mit.edu/publication/MIT_CISRwp439_PepsiCoDX_Wixom.

18 E. Alfaro, J. Murillo, F. Girardin, B. H. Wixom, and I. Someh, "BBVA Fuels Digital Transformation Progress with a Data Science Center of Excellence," MIT Sloan CISR Working Paper No. 430, May 2018, https://cisr.mit.edu/publication/MIT_CISRwp430_BBVADataScienceCoE_AlfaroMurilloGirardinWixomSomeh.

19 B. H. Wixom and R. Schüritz, "Creating Customer Value Using Analytics."

settings to deliver the best hearing for the conditions. Changes to processor program settings had previously been made manually by the patient, but product use data suggested that patients might not have always chosen the optimal settings for the situation. The developers created a scene classifier algorithm that recognized distinct contexts and made tailored processing adjustments.

CONCLUSION

AI techniques have been maturing for decades, but only recently have synergistic advances in technology, availability of data, and data science skills propelled AI into the mainstream. The market, however, still lacks a broad selection of proven use cases. It is not surprising, therefore, that leaders are uncertain regarding how and if their company can create meaningful returns from AI project investments. Add to that the negative press about the use of AI models and it is not surprising that leaders consider AI a risky bet.

Based on MIT CISR research, we view AI as a requisite competency for the algorithmic economy—and a phenomenon that companies need to explore and learn. AI competency building requires that business leaders advance their data monetization capabilities—and invest in the new AI-specific capability we call explanation. In the upcoming phase of our research, we will identify exactly how companies are doing this today.

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