Overcoming Organizational Obstacles to Artificial Intelligence Project Adoption: Propositions for Research

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Abstract

Artificial intelligence (AI) is the next technology revolution, and one which offers huge potential benefits for companies around the world. In fact, companies that learn how to adopt AI effectively will be positioned to maximize value creation using data in the emerging algorithmic economy. Uptake of AI has been limited, however, and there are mounting associated concerns. This paper explores what companies need to better understand about AI adoption so they can make the most of this transformational phenomenon. The paper develops a framework and an associated research agenda intended to motivate practice-based research that will help business leaders advance their AI efforts

1. Introduction

Artificial Intelligence (AI) represents a set of technologies that seek to mimic human ability to find patterns in data, make predictions and find recommended actions without explicit human instructions [1]. What distinguishes AI from predictive and prescriptive analytics is AI's ability to self-learn and to process natural language [2]. AI can autonomously conduct tasks and engage with people – for example, social bots chatting to customers or Uber algorithms giving instructions to drivers.

AI investments have increased in recent years. In the US, investments in AI-related companies rose by 72 per cent in 2018 to reach $9.3 billion [3]. Some thought leaders tout AI as the next general-purpose technology, which has the potential to create considerable economic growth and follow similar patterns as the steam engine and electricity [1], [4], [5]. There is emerging evidence that AI can create value for organizations by reducing process costs, enabling new revenue streams, and increasing product sales. According to the McKinsey Global Institute, at a 'global average level of adoption,' AI could deliver 1.2 percent additional GDP growth annually.

Despite promising AI trends and forecasts, organizational adoption of AI remains low; only 20 per cent of AI-aware companies are currently using AI in a core business process or at scale [2]. The literature highlights a number of **societal reasons** for slow AI adoption. For example, the value of AI is not clear to many stakeholders, as it can cause negative externalities through activities such as extensive individual profiling and algorithmic decisions, which can threaten privacy and can cause discrimination [6]. Also, AI's ability to replace humans or reshape human work tasks has implications for workforce employability and the changing roles of workers, such as domain experts (e.g., doctors, engineers, financiers or other specialists) who have deep knowledge and experience within their fields [1], [7].

The literature currently sheds less light on **organizational reasons** for slow AI adoption; information systems research on the topic, for example, is scant and mostly anecdotal in nature [8]–[10]. Arguably, researchers can draw upon decision support and other related literature to propose and study how organizations can effectively deploy AI. However, AI's contemporary contexts, novel characteristics (e.g., self-learning and autonomy) and its potential to create unintended consequences suggest that there are nuances about AI that must be explored using present-day, AI-specific research efforts. Such efforts are required before business leaders can deeply understand AI adoption - and the acceptable approaches through which AI can create value. Thus, we ask the following research questions: *What are the organizational obstacles for AI adoption?*

We view AI adoption as necessary but not sufficient for value creation. Thus, this paper presents a framework that identifies obstacles for AI adoption within a value creation context. we use the framework to set high-priority practice-based AI research directions; the framework informs both IS scholars who intend to investigate how organizations can best increase adoption of, and ultimately value from, AI and business leaders who hope to exploit AI in fruitful, acceptable ways. In the following sections, we first use

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the framework to organize data about AI obstacles that we collected from senior executives. Next, we share descriptions of six AI projects that reinforce and further inform AI obstacles, and then we present resulting propositions for AI research. We close with a brief discussion of implications.

2. Creating Value from Artificial Intelligence

2.1. Recent Evidence on AI Value

AI offers huge potential benefits for organizations. The phenomenon enables contemporary data and analytics efforts that generate value in myriad ways, ranging from improving business process efficiency and accelerating medical research findings to operating smart cities and serving customers with innovative digital solutions [8]. In our own recent case studies, AI was used by Microsoft to streamline the enterprise sales process by predicting the likelihood of a sale to close [11], by Cochlear to improve the sound experience of hearing implant patients by identifying sound contexts and automatically adjusting sound device settings [12], and by BBVA to help banking customers manage personal finances by predicting future transactions and categorizing spend [13]. These types of positive AI outcomes and the wide range of benefits they represent are consistent with AI value communicated in the popular press [2], [8].

2.2. Framework on AI Value

Figure 1 represents a process-oriented view of how AI creates value for organizations, which we term the AI Value Framework. We developed this framework by extending an existing practice-based framework on generating value from big data [14] that we use regularly to teach executive education classes. We find that the framework resonates with practitioners and helps them understand key concepts associated with data value creation and obstacles. For this study, we extended the framework by drawing on recent case studies and recent literature specific to AI [8], [15]–[17]. Specifically, the framework was changed by 1) adding additional AI and organizational resources that the initial framework did not explicitly include and 2) organizing concepts by project level and organization level. We assumed that AI adoption obstacles potentially could occur at any point across the value creation process.

2.2.1. AI Projects. The framework communicates that organizations create AI value at the project level by following four distinct steps: (1) formulating a business purpose, (2) generating meaningful insights from the data, (3) taking actions based on the insights, possibly in the form of automated business processes, and (4) realizing project value [14]. The project is enabled by three key AI organizational resources (i.e., data, platform and talent) and by three complementary organizational resources (i.e., leadership, domain knowledge, and governance), all of which can be shaped by project activities as they are executed. AI projects might be narrow in focus (e.g., automating a granular sales task) and for this reason, execution of multiple AI projects over time generate overall organizational value.

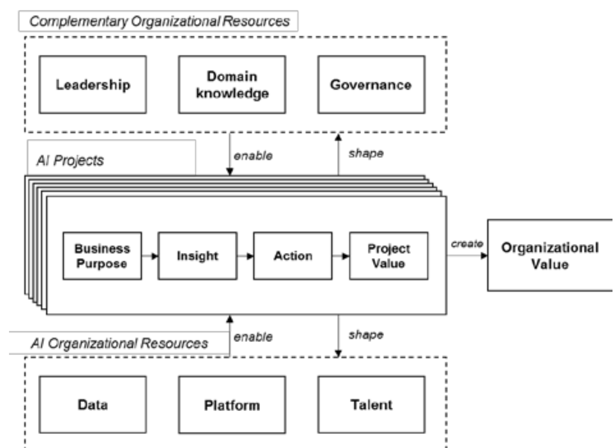

Figure 1 AI Value Framework

2.2.2. AI Organizational Resources. Value creation at the AI project level depends on AI organizational resources, which are a subset of the organization's overall resources; specifically, three AI organizational resources are required for AI project execution. **Data** includes a range of structured and unstructured data sets sourced from internal and external systems that can be used to formulate and train AI algorithms. **Platform** includes technology and processes required to manipulate the data sets and to access and distribute data and analytics services. **Talent** refers to data scientists who specialize in building and working with algorithms that predict, classify or cluster data.

Every time an AI project is executed, the knowledge created by the project further shapes the AI organizational resources. For example, data scientists assigned to improve customer retention with AI can develop a novel churn algorithm, which subsequently can be integrated into a platform and get reused for other projects.

2.2.3. Complementary Organizational Resources. Complementary organizational resources are a set of non-IT factors – leadership, domain knowledge and governance – that facilitate organizational adoption and diffusion of AI [18]. **Leadership** represents the organization's vision and commitment to AI. **Domain knowledge** is the know-how of experts in areas of content to which AI will be applied such as employee retention, marketing segmentation, and supply chain optimization. **Governance** includes mechanisms by which AI-related decisions and processes are managed in ways that benefit organizational stakeholders and minimize risks. Complementary organizational resources typically are associated with changes to organizational design, business models, processes and rules, culture and legal requirements, and they are necessary for pervasive, responsible AI use [1], [19].

3. Research Method

3.1. Executive Discussion

In order to validate the usefulness of the framework, we convened an online discussion with the members of the MIT Center for Information Systems Research Data Advisory Board in Quarter 1 of 2019. The Board consisted of 95 data executives representing 67 large companies headquartered around the globe. Most organizations were multi-national and for-profit, and the executives held Chief Data Officer, Chief Analytics Officer, or equivalent roles.

Each executive was asked to answer the following question in an online discussion board (they were given a deadline of one month to submit responses):

- *What are the top three impediments to AI adoption/consumption in your company?*

Along with the question, we provided the executives with the following AI definition:

> *"Definition: Artificial intelligence (AI) is a set of technologies that seeks to mimic human ability to understand data, find patterns, make predictions and find recommended actions without explicit human instructions. What distinguishes AI technology from traditional predictive and prescriptive analytics is (1) its ability to self-learn and (2) its ability to process natural language (source: Gartner Trend Insight Report* [20]*)."*

Ultimately, 53 data executives from 50 organizations answered our question, resulting in a 75 percent response rate (we only required one answer per organization). Several respondents provided artifacts (e.g., internal company reports, decks) to support their answers. Some of the non-respondents specifically explained that their lack of response was due to lack of AI activity at their organization.

Two researchers analyzed the board answers using thematic content analysis to identify common patterns and emergent themes [21] and to create a list of AI obstacle categories. Then, we iteratively matched these categories with components of the AI value framework. See Tables 1-3 for the results of this process. Each table lists the distinct obstacles that the team identified, representative evidence, and the number of board members who contributed the obstacle in their response.

Table 1 AI Adoption: Project Obstacles

Obstacle/Evidence	Cnt
Business Purpose: Compelling Business Objective *"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."* *"Use cases with a clear return on investment for the business."*	22
Insight: Development *"[Minimum viable product] and agile development and deployment."* *"Create an environment where we can experiment and fail fast. Learn from previous experience and fine-tune going forward."*	6
Action: Fear and Mistrust *"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 limits or removes human interaction."* *"Inability of certain complex models to explain the outcomes. Models that cannot provide explanation of recommendations are unlikely to be adopted."*	8
Action: Process Integration *"Integration with legacy systems that may be required to consume the AI algorithms by the business."* *"Cadence of deploying AI models and fully integrating them into core business processes."*	8
Action: Culture *"The culture of using data to drive decisions, leading to ignorance on what data can solve for."* *"Focus on the present, not the future; current-year operational and financial performance metrics that focus on aggressive performance in the current year, rather than the next five years."*	9
Project Value: Value *"Value demonstration at scale."* *"Proving out the resulting value."*	8

Table 2 AI Adoption: Organizational Resource Obstacles

Obstacles/ Evidence	Cnt
Data: Training Data Sets *"Huge volume of continuously fresh data to establish a model and mature it via learning algorithms."* *"Lack of transaction data on which to train."*	3
Data: Data Quality *"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."* *"Data quality; data that has missing elements and data that is corrupted in systematic ways."*	29
Data: Data Structures *"Working with external data sources that follow different taxonomies than the ones used at [my company]."* *"Confusion regarding terminology and definitions is fracturing our progress. A common lexicon can enable groups to work together more and make more progress."*	7
Platform: AI Platform *"Need for new architectures and technologies not used in the traditional company."* *"Scalable processing power."*	19
Talent: AI Talent *"Skills. 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. All three of these steps need specialist skills at a relatively high level. We don't have many people who can effectively select and use algorithms."* *"Skilled technical people who understand our processes, data, and the AI technologies."*	25

Table 3 AI Adoption: Complementary Organizational Resource Obstacles

Obstacles/ Evidence	Cnt
Leadership: Top Management Understanding/Support *"Lack of executive understanding of what AI takes."* *"[Our executives] all hear about it, 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."*	14
Domain Knowledge: Domain Engagement *"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."* *"Lack of skills and expertise in the business areas to engage with, to identify what problems could be solved through AI capabilities."*	4
Governance: Acceptable Data Use *"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."*	6
Governance: Enterprise Strategy *"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)."* *"Development of a unified data strategy that is endorsed and actively supported and integrated across the entire business."*	8

The executive discussion helped the research team in two important ways. First, the process identified **common AI obstacles**; data quality, AI talent, compelling business objective, and AI platform were most often repeated across board member responses. Second, the process identified obstacles that were **unique to AI**; fear and mistrust, training data sets, acceptable data use, domain engagement, and AI talent represent obstacles that do not traditionally surface as data obstacles (such as those in [14]).

3.2. Project Description Review

To better understand the AI obstacles that were categorized into Tables 1-3 and to further validate their importance, the authors explored descriptions of actual AI projects conducted in conjunction with a professional services firm (i.e., a set of client engagements). The firm, Alix Partners, is a global consulting organization that established a practice in AI in 2015. In four years, the practice has participated in 85 engagements that involve AI. Recently, the practice confidentially inventoried key projects for internal knowledge management purposes. One member of the research team, the managing director of this practice, reviewed the inventory of 85 engagements and identified a representative sample of six for the full research team to analyze. The purposeful sample was created to showcase a diverse set of companies across industries, in which a wide set of AI obstacles had been overcome. Short descriptions of the six engagements are included in the following sections. Note that three of the engagements (C, D and E) were also described in a book authored by one of the authors [22]. Within each description, we indicate the AI obstacles for the reader in brackets.

Health IT Company A

Company A, the result of the merger of two previous companies, provides full-payment-lifecycle assurance services to healthcare clients, and the combined entity has annual revenue of over $1B. Company A wanted to differentiate itself by using AI across the enterprise to gain market share by processing claims faster and improving the quality of payments results, increasing revenues by identifying a larger percentage of bad claims, and reducing labor through automation of claims processes and integration of shared services. For training data sets, the company relied largely on over 3 petabytes of historic US healthcare claims data.

In implementing its AI strategy, Company A encountered technical obstacles [AI Platform], but found leadership [Top Management Understanding/Support] and talent [AI Talent] more difficult to overcome. To overcome the obstacles, the company educated its senior management about AI. It hired data science and data engineering talent and created a new engineering organization to build the modern AI platform and models. It stood up a new shared services group to reengineer processes [Process Integration] to execute AI-based insights through workflow solutions. To prove the value of AI along the way and win over skeptics [Compelling Business Objective], the company created its AI capability incrementally, moving one category of claims to the new platform at a time and implementing claims review concepts one group at a time, with the most valuable ones first.

Home Services Company B

Company B is a provider of home services including HVAC, electrical, and plumbing with annual revenue of over $300M. It has an advantageous position in the field service ecosystem at the intersection of the customer, OEMs, and service technicians. Company B set out to build an AI capability to strengthen its customer relationships across existing and new brands, create a comprehensive view of the customer to personalize offerings using internally collected and externally acquired data, and develop a scalable AI platform based on modern technologies to enable current and future AI use cases across business functions. Company B had grown through multiple acquisitions, resulting in a variety of data sources and formats, and had never combined all of its data together before, which created obstacles for creating a single source of truth for customer data [Data Structures, Data Quality]. It also had a highly decentralized workforce with limited knowledge of AI and inconsistent access to data and decision tools [AI Talent, AI Platform].

The company convened its executives for a digital strategy and roadmap workshop to agree on short, medium, and long-term goals. It also held multiple deep dive sessions for leaders to understand the company's data, as well as the inner workings of the AI models. It hired expertise in both data science (to build and maintain models) and data engineering (to expand and manage the digital platform). To prove the value from AI [Value], the company measured the results from customer interactions and also developed business cases for over $50M in gross margin enhancement opportunities across multiple areas.

Location Analytics Company C

Company C is a start-up company founded in 2011 in San Francisco. Its technology uses mobile phone WiFi signals and spatial analytics to provide stores and restaurants with unique customer location insights. In 2019, the company was acquired by a 5,000-employee shared workspace company with the intent of using the technology to increase collaboration and productivity based on employee location data.

From the beginning, Company C recognized that handling people's personally identifying data in an ethical way was imperative. This was a challenging goal, given the nature of its business: recording data emanating from smartphones in retail stores and using data science to supply retailers with the resulting aggregated data [Acceptable Data Use]. Smartphones send a constant stream of pings to connect with WiFi networks, even when the phone owner is not aware of it. Company C can collect that phone data and infer all kinds of insights about individual behavior.

Company C's business caught the attention of both the public and the US Congress; and it became a public imperative to create rules in the location analytics space [Acceptable Data Use]. Although Company C was using data in a conservative manner from a privacy perspective, it was believed that other companies may not follow suit. Company C hired a privacy expert from Stanford University and adopted "privacy by design" principles. The company also worked with seven competitors, the Future of Privacy Forum, and the Federal Trade Commission to create a code of conduct for "locational analytics."

Auto Parts Manufacturer Company D

Company D was a start-up founded by Google engineers, bought by a mobility service company in a $680M deal in 2016, and subsequently shuttered in 2018 after failing to meet performance targets. It offered a self-driving kit for long-haul trucks to automate driving tasks. The device included cameras, radar, cutting-edge sensors, as well as controls for power steering and redundant braking, all powered by AI algorithms.

Company D had some success, and one of its self-driving trucks made a successful first delivery of approximately 50,000 cans of beer. However, the company continued to face regulatory obstacles [Acceptable Data Use] and technical obstacles, including lack of sufficient training data to build AI models capable of handling complex situations like bad weather and city driving [Training Data Sets]. To overcome some of the obstacles with training the AI models, Company D hired career truck drivers to augment training data with experience.

Biopharmaceutical Company E

Company E is a global leader in the making of human vaccines, with annual revenues of over $40B. Vaccine manufacturing includes many steps, including growing yeast, agitating, fermenting, and purifying. The manufacturing process is highly variable, and if something goes awry, the entire batch must be thrown out. Company E had extensive data about the vaccine line, including ten years' worth of data from thousands of sensors including shop floor processes, plant equipment maintenance, and building environment sensors that measured air pressure, temperature, and other factors by the minute. By implementing AI, the company was able to conduct a large-scale analysis of its terabytes of data using 15 billion calculations and more than 5.5 million batch-to-batch comparisons. It created heat maps showing data clusters associated with high and low yields. However, validating the insights was challenging and needed expert involvement [Domain Engagement].

Company E allocated experts to examine the heat maps, recommended changes, reworked predictive models, and run more analyses to identify problematic factors. Implementing AI also required an experimentation approach and a shift in mindset from reactive to proactive manufacturing intelligence [Development]. Company E realized significant savings in the vaccine-making process while protecting considerably more lives. Demonstrating success with the vaccine line helped with change management and convinced leaders to expand the concept plant-wide and also into other plant.

Retail Industry Company F

Company F is a leading global sourcing and logistics provider for the retail clothing industry with over $10B in annual revenue. The company's business performance had worsened significantly in the distressed retail environment, causing decreases in both net income and stock price. The company undertook a comprehensive assessment of business opportunities, digital and AI strategy, and organization structure, resulting in a set of initiatives to increase speed to market, create new service offerings and enable new ways of working. Company F created a "Digital Transformation" business unit, integrating business and technology staff, to develop complementary roles between AI and domain experts who would carry out the new digital roadmap and AI efforts.

The company started by building, piloting, and rolling out to customers, a first set of over twenty digital applications, including AI-enabled insights for material management, 3D design, design workflow, capacity management, product trend insights, and cost modeling. The company established new digital operations groups for key areas such as 3D design, product design collaboration, digital material management, and customer technical integration to absorb and support the applications [Domain Engagement]. Also, the company hired [Top Management Understanding/Support] a new Chief Digital Officer (CDO), enterprise architect, product owners for key digital offerings, and core software development staff, and it established a governing structure for the new digital transformation unit that consisted of a program management office, executive oversight, vendor management, digital product structure, and metrics and reporting.

The six engagement descriptions support the AI obstacles provided by the executives, and in fact, they begin to shed light on how companies are finding ways to address obstacles. Table 4 lists solutions that the research team was able to associate with specific obstacles.

Table 4 Engagement Solutions to AI Obstacles

AI Project Obstacles and Solutions	
Compelling Business Objective	Establish small wins by rolling out AI incrementally [A], Sequence high-value projects first [A], Establish lucrative business cases [B]
Development	Support experimentation [E], Pilot test AI projects [F]
Fear and Mistrust	Teach leaders how AI models work [B]
Process Integration	Create a process reengineering unit to embed AI insights into workflow [A], Communicate success [E]
Culture	Encourage proactive problem-solving instead of reactive [E]
Value	Measure results from customer interactions [B]

AI Organizational Resource Obstacles and Solutions	
Training Data Sets	Use domain experts to improve or fill gaps in training datasets [D]
Data Quality	Teach leaders about data [B]
Data Structures	Teach leaders about data [B]
AI Platform	Create an engineering unit to build an AI platform [A]
AI Talent	Hire new data science and data engineering talent [A] [B]
Complementary Organizational Resource Obstacles and Solutions	
Top Management Understanding/ Support	Educate top management about AI [A], Hire executives to lead transformation projects [F]
Domain Engagement	Assign domain experts to review, validate and manage AI-based insights [E], Establish operations group with strong business ties [F]
Acceptable Data Use	Use data conservatively [C], Hire privacy expertise to shape work practices and policies [C], Adopt privacy by design principles [C], Engage with industry stakeholders to shape public policy and industry regulation [C]
Enterprise Strategy	Engage executives in workshops to roadmap and set goals [B]

4. Overcoming AI Obstacles

As the research team analyzed AI obstacles provided by executives and described within the project descriptions, we observed that many obstacles reflect challenges that have been common to data projects for decades. For example, two common obstacles – lack of a compelling business objective and poor data quality – have plagued data projects since the early days of computing. The team also observed, however, that some AI obstacles appear to be more common or more important in today's chapter of AI projects. These obstacles include training data sets, fear and mistrust, domain engagement, acceptable data use, and AI talent. Thus, we used these obstacles to develop an initial set of propositions regarding areas of AI that we believe should receive high-priority practice-based research attention. We next describe these key contemporary obstacles and associated propositions.

The Obstacle of Data: Training Data Sets

In contrast with business intelligence and business analytics approaches, AI approaches draw upon algorithms that are trained, or taught to perform specific tasks (rather than programmed). Training happens by processing large sets of data [23]; therefore, algorithms are vulnerable to the underlying data. For example, historical data might be biased towards minorities [16], [24] and train biased algorithms; Microsoft's AI algorithm learned to become racist by conversing with other users on Twitter, and in another case an algorithm earned to become biased towards black people when AI was used to predict prisoner recidivism risk [24], [25]. Therefore, companies must learn how to extend or create processes that source, build and manage training sets so that related obstacles can be removed. Further, companies may need to find ways to fill gaps when training sets fall short. In Auto Parts Manufacturer Company D, career truck drivers were used to augment training data with experience and help shape the algorithms for complex scenarios like bad weather.

Proposition 1: AI practice-based research is needed to explore how companies can prevent bias and address shortcomings in training datasets.

The Obstacle of Action: Fear and Mistrust

The reasoning and process behind AI-based decisions may be opaque [5]. Deep learning algorithms, in particular, autonomously learn from example data, and propagate their learning across various network layers [10]. This makes it difficult for domain experts to understand how AI works and to trust outcomes. In some cases, high dimensionality of the data (i.e., the number of features or attributes used in data analysis) makes it difficult for users to understand algorithm outcomes in a meaningful way [26].

For algorithmic decisions to be transparent and trustworthy, humans need to understand how and why a certain decision was made. This can be achieved if AI experts design traceable algorithms and/or if domain experts can provide justification based on deep domain knowledge [27] or triangulation of methods [25]; otherwise, humans cannot guarantee that decisions are non-discriminatory or meaningful in real world contexts. At Home Services Company B, the researchers were struck by the company's desire to create algorithmic transparency and trust even at the highest levels of the organization; for example, the company held deep dive sessions for its executives to understand the inner workings of the AI models.

Proposition 2: AI practice-based research is needed to explore how and to whom companies can best explain, communicate, and/or justify algorithmic decisions.

The Obstacle of Domain Knowledge: Domain Engagement

AI projects require a break with conventional development in that domain experts who are field specialists and who traditionally set the business rules that IT systems are designed support no longer are in control; instead, AI projects include rules generated from data and acted upon by machines. This shift in rule-making dynamics makes it critical to reimagine the relationship between domain experts and the AI experts who design and write algorithms.

AI and domain experts fundamentally share one of two types of relationships [28]: (1) complementary when AI and domain experts augment one another, and (2) substitution when AI and domain experts replace one another. An example of a complementary relationship is when domain experts take a "trainer" role and teach the algorithm how the world works [15]. Another example occurs when domain experts oversee the algorithmic learning process and ensure correctness and fairness. Organizations likely need to reshape or create roles and responsibilities for domain experts (and their algorithm counterparts) so that domain knowledge properly manifests within an AI project. After implementing AI, Biopharmaceutical Company E assigned new roles to vaccine experts to conduct comparisons using large scale datasets (which was impossible for domain experts to do manually). The experts became responsible for examining, reworking and improving AI models.

Proposition 3: AI practice-based research is needed to explore the substitutive and complementary, new and changing roles of domain and algorithm experts.

The Obstacle of Governance: Acceptable Data Use

AI-based algorithms potentially can act unethically and create negative externalities for individuals and society; consider the concerns of privacy, extensive profiling of individuals, biases or discrimination [6], [29]–[31]. Companies must develop algorithms that act in acceptable ways, and they must infuse ethics systematically into their organizational fabric [32]. Otherwise, companies will encounter risks of deploying AI projects that act in undesired or wrong ways, which can result in financial losses, reputational damage, or increased regulatory or other constraints.

Traditional data projects are governed so that they comply with regulatory and legal constraints; however, for AI, this form of governance is necessary but not sufficient. Governance of AI projects must consider and address values of the company and both its direct and indirect stakeholders [33]. Location Analytics Company C adopted privacy by design principles to develop their services. This helped the company incorporate human values throughout its development process.

Proposition 4: AI practice-based research is needed to explore acceptable data use governance, which extends oversight of AI projects beyond regulatory and legal compliance.

The Obstacle of Talent: AI Talent

Analyst firms have predicted both the importance of and dearth of data science talent for the past decade [34]. The increase in AI applications will only exacerbate this talent shortage. Further, not only is the number of AI applications increasing, but also the number of business tasks that include and are impacted by AI. Without changes to current talent attraction, development, reskilling and upskilling practices, acquiring AI talent will become a serious bottleneck in AI adoption and consumption within organizations.

AI talent also needs to be reexamined regarding exactly what it represents. Beyond the ability to build, train, interpret, and deploy models, data scientists who specialize in AI will need a diverse skillset that likely includes skills like storytelling, visualization, data taxonomies and structures, ethics, and value-based design. In a recent survey of AI organizational challenges, half of the leaders surveyed indicated that they need machine learning experts who can identify AI identify use cases that lend themselves to AI solutions [35]. Companies will need to craft creative new workforce strategies that may include ideas such as increasing investment in upskilling existing employees or creating new business units specifically to attract and cultivate AI talent. Health IT Company A and Home Services Company B both started their AI journeys by hiring new data science and data engineering talent to build AI models and AI platforms.

Proposition 5: AI practice-based research is needed to explore AI talent requirements for companies – and how to build effective new talent strategies, portfolios, and management programs.

5. Discussion

Despite its potential, AI adoption and consumption needs research attention before practice can advance. We propose a framework and a set of research propositions that articulate high-priority, practice-based AI research directions. The propositions require innovative research efforts that integrate and extend – yet also break away from – past literature and thought on value creation from data.

Our paper has several implications for readers to consider. First, we provide a **process-oriented framework on AI value** that identifies AI and complementary organizational resources and the process by which these resources can be assembled together within AI projects to create value for organizations. Second, our paper identifies **obstacles to AI adoption** and offers a **research agenda for practice-based research**. The research agenda was informed by executives from around the world who are leading AI teams and who are accountable for AI success – and by descriptions of actual AI engagements that have happened within the past few years. We provide a summary of our research propositions in Table 5.

Table 5: Summary of Research Propositions

Proposition
P1: AI research is needed to explore how companies can prevent bias in training datasets.
P2: AI research is needed to explore how companies can best explain, communicate, and/or justify algorithmic decisions.
P3: AI research is needed to explore the substitutive and complementary roles of domain and algorithm experts.
P4: AI research is needed to explore acceptable data use governance, which extends oversight of data projects beyond regulatory and legal compliance.
P5: AI research is needed to explore AI talent requirements for companies – and how to build effective new talent strategies, portfolios, and management programs.

We encourage researchers to adopt creative, interesting approaches to refine and explore the framework and research propositions with the intent of generating relevant, applicable managerial insights. We suggest possible approaches as examples:

- Qualitatively investigate how AI and humans (e.g., domain experts) can complement each other or act as an integrated unit by interviewing project team members across a series of AI projects. Researchers could use grounded theory to develop novel conceptualizations and communicate implications.
- Quantitatively measure AI value creation within organizations. Ideally, a value measurements study would examine AI value across stakeholders and explore both positive and negative AI impacts.
- Employ social network or configurational research approaches to explore AI and human relationships. Specifically, configurational approach combines the strength of both qualitative and quantitative methods [36] and can help build AI-human configurations by identifying combinations of attributes that together lead to different types of relationship outcomes; this approach is rarely applied in IS research [37].
- Explore AI ethics using a scenario method, an approach commonly applied to study business ethics. In a review of 174 ethical decision-making articles published in premier business journals, 55 percent employed a scenario approach [38]. We view its use to explore AI ethics as promising.
- Finally, investigate AI externalities using socio-material approaches to take into account AI-human entanglement and performativity of AI technology [39]. This approach would consider employee's repeated and situated interaction with AI and how behavior is organized around and facilitated by AI.

6. Conclusion

AI is high on executives' agendas. It potentially can generate big value; yet, if not appropriately deployed and nurtured, can fall short and, worst case, cause harm. From our own interactions with executives, many are unclear regarding AI's true value potential given current obstacles and unknowns. Our research framework provides a comprehensive view of the AI value creation process, and it helps communicate obstacles that organizations face today. We encourage researchers to begin investigating our set of propositions. And, while researchers work to advance understanding in this space, we hope that our framework can help executives focus their investments, management attention, and remediation activities. Moreover, we document (in Table 4) an initial set of helpful practices that practitioners may want to consider as they initiate AI projects.

7. References

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