Capturing Value from Artificial Intelligence

Justin M. Berg
Stanford University
jmberg@stanford.edu

Manav Raj
University of Pennsylvania
manavraj@wharton.upenn.edu

Robert Seamans[1]
New York University
rseamans@stern.nyu.edu

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Abstract: In this *AMD Guidepost* essay, we document outstanding questions regarding how organizations can capture value from AI tools and outline pathways for future exploratory management and organizational research on AI. Specifically, we emphasize the importance of understanding how advances in AI technologies may reshape how organizations develop and use complementary assets. We highlight this point using the recent case of ChatGPT, an AI-enabled language modeler released in November 2022 that has grown in popularity more quickly than any other consumer application, including TikTok and Instagram.

Keywords: artificial intelligence; complementary assets; creativity; strategy; technology

[1] Corresponding author. Authors listed alphabetically; all authors contributed equally. The authors thank Kevin Rockmann and Joachim Henkel for valuable feedback.

INTRODUCTION

Artificial Intelligence (AI) has developed rapidly over the past decade. The improvement in AI has taken place across a variety of domains, as evidenced by advances in image recognition, speech recognition, language modeling, abstract strategy game playing, and other areas.[2] AI is also being commercialized rapidly. According to the OECD, investments in AI startups accounted for over 20% of all venture capital investments in 2020, up from less than 5% in 2012.[3] Further, corporations are investing in more AI, though with mixed success, as bluntly highlighted by the following article title from the *Economist*: "Businesses are finding AI hard to adopt."[4] As AI technologies continue to advance, it has become increasingly important to understand how organizations can use AI tools to create and capture value.

In this *AMD Guidepost* essay, we document outstanding questions regarding how organizations can capture value from AI tools and outline pathways for future exploratory management and organizational research on AI. Specifically, we emphasize the importance of understanding how advances in AI technologies may reshape how organizations develop and use complementary assets. We highlight this point using the recent case of ChatGPT, an AI-enabled language modeler released in November 2022 that has grown in popularity more quickly than any other consumer application, including TikTok and Instagram.[5]

RAPID CHANGES: THE CASE OF CHATGPT

The release of ChatGPT in November 2022 highlights the rapid advance of AI technologies, highlighting that such advancement is not necessarily continuous but can occur in sudden bursts. ChatGPT is a language modeling AI system developed by OpenAI that takes

[2] https://www.eff.org/files/AI-progress-metrics.html
[3] https://oecd.ai/en/vc
[4] https://www.economist.com/technology-quarterly/2020/06/11/businesses-are-finding-ai-hard-to-adopt
[5] https://time.com/6253615/chatgpt-fastest-growing/

prompts from a user and then provides a response. For example, a user could provide the following prompt "write a 1,000-word essay on AI and complementary assets" and ChatGPT would then provide such an essay within a few moments. The speed and sophistication of ChatGPT relative to similar language modeling systems in the past has captured the imagination of the general public, caused worry among educators (who fear students relying on ChatGPT to write homework essays), and excitement among businesses. Notably, Microsoft announced a $10 billion partnership with OpenAI and has linked ChatGPT with its Bing search engine.[6]

Part of the excitement linked to ChatGPT and tools like it is due to the ability to apply AI in a variety of domains. These include the production of descriptive or creative written output (Noy and Zhang, 2023), evaluation of human-generated input (Christodoulou, 2023), ideation or creative problem solving (Mollick, 2022), and assistance with programming or coding (Peng et al., 2023). The broad applicability of ChatGPT has led to the rapid adoption of the tool and its use across industries. OpenAI currently makes money from ChatGPT via a premium subscription, as is the case with other generative AI tools such as ChatSonic, Midjourney, DLL-E 2, Replika, and Jasper.[7]

The emergence of this technology makes salient the distinction between two different kinds of AI technologies: generative and discriminative AI (Jebara, 2004). Discriminative models are best suited for classification and prediction tasks, while generative models are best suited for tasks that generate new data (Jebara, 2004). Thus far, much of the research that has outlined complementary assets to AI tools has focused on one kind of AI tool – discriminative AI tools that are used to make predictions and categorize content (Jebara, 2004). Generative AI,

[6] https://www.bloomberg.com/news/articles/2023-01-23/microsoft-makes-multibillion-dollar-investment-in-openai
[7] A number of generative AI tools have been made broadly available for free, including Bing Chat, YouChat, and Google Bard.

such as ChatGPT, can be used to produce content, rather than analyze it. The recent advances in generative AI tools has re-generated excitement in AI technologies and broadened the scope of uses for which AI may be suitable (Berg et al., 2023).

Areas For Further Research: Complementary Assets and AI

Scholars refer to technologies such as AI that can be used in multiple ways across industries as general purpose technologies (Lipsey et al., 1998; Goldfarb et al., 2023). Historically, general purpose technologies only provide value to organizations that also invest in complementary assets to harness the power of the new technology (David, 1990). The fact that (1) AI is developing so rapidly–as made apparent by the case of ChatGPT–and that (2) organizations need to invest in complementary assets to take advantage of the AI that they are adopting, poses important research questions for management scholars interested in this domain. How is generative AI affecting the nature of work across different occupations? In what ways should organizations adapt to address the changing ways that workers are using generative AI? How do organizations determine what complementary assets they should invest in? Should organizations invest now in AI and the requisite complementary assets at the risk of being outdated in a few years? Or, should organizations wait to invest in AI and the necessary complementary assets at the risk of missing out on gains from such a new technology? Below, we outline these and other questions that require future research.

Do different kinds of AI require different complementary assets? In the case of AI, the complementary assets most often discussed are talent, computing power, often called “compute”, industry knowledge, and data. The human capital skills important for AI currently include software and coding skills, tailored to whatever the firm does. The value of individuals with these top skills became apparent towards the end of the 2010s when various news articles highlighted million-dollar salaries at firms like OpenAI, Google and others.[8] Further, industry knowledge enables firms to take broad-based AI tools and apply them to generate value in specific contexts.

The digital capital necessary for AI includes the algorithm created by the programmer and the data needed to train the algorithm, and use it. Hartmann & Henkel (2020) argue that data is a strategic resource that in part explains why large tech firms invest considerable sums in performing and publishing basic research in the field of AI, and apparently profit from it. Bessen et al. (2022) show that startups with access to proprietary training data are more likely to acquire venture capital funding.

However, the rapidly expanding scope of what generative AI technologies can do has implications for what complementary assets may be more or less important to ultimately capture value from these technologies. To illustrate this, we highlight recent findings from Felten et al. (2023), who update a framework developed in Felten et al. (2021) that assesses which occupations and industries are most exposed to the recent advances in AI language modeling. Table 1, taken from Felten et al. (2023), provides the list of top 20 occupations exposed to the recent advances in AI language modeling.

Insert Table 1 Here

The list of top exposed occupations includes many education-related occupations, indicating that occupations in the field of education are likely to be relatively more impacted by advances in language modeling than other occupations. This accords well with the recent spate

[8] For examples, see this article in Forbes: https://www.forbes.com/sites/samshead/2018/04/20/ai-geniuses-are-being-paid-over-1-million-at-elon-musks-openai/ or this one in Seattle Times: https://www.seattletimes.com/business/ai-researchers-are-making-more-than-1-million-even-at-a-nonprofit/

of articles around how ChatGPT and other language modeling tools affect the way teachers assign work and detect cheating or could use language modeling tools to develop teaching materials.

Of special interest is that the top occupation in Table 1 is “telemarketer.” One might imagine that telemarketers could benefit from language modeling because customer responses can be fed into a language modeling engine and relevant prompts quickly fed to the telemarketer. Or, maybe the need for a human telemarketer diminishes, as the automated language modeler can be trained to respond to whatever the potential customer says.

As these examples highlight, changes in the scope of AI technologies may change what kinds of human capital in organizations are most affected. Even if it is not clear if these changes mean that the human capital is becoming more or less important, it is apparent there will be changes in the relative importance of certain human capital. This illustrates that different kinds of AI technologies may affect human capital differently and may require different kinds of complementary assets. Future research that explores the distinction between generative vs. discriminative AI may be able to provide greater insight on how different kinds of complementary assets may be better suited for one type of AI technology vs. the other. For example, with discriminative AI, the keys to unlocking performance may be data and highly skilled data scientists to leverage said data—because the problems discriminative AI solves are “close-ended." For generative AI, because the potential uses are virtually limitless and open-ended, there may be more of a premium for creativity and the ability to identify how to use these tools well.

How do organizations manage AI technology evolution? As noted in the example of ChatGPT, AI technology has shown the potential to advance rapidly in terms of scope and sophistication. Such advances can lead to unstable or rapidly changing industry environments, posing challenges to organizations. Future work is needed to understand how organizations manage such environments. A useful starting place to develop an understanding about how organizations will manage rapid changes from AI is to look to past episodes of rapid advancement of technologies including electrification (David, 1990), telephone (Feigenbaum and Gross, 2022) and internet (Mowery and Simcoe, 2002; Schilling 2015). One is often tempted to consider a new technology and its implications as something never seen before, while in fact the underlying dynamics are the same as for earlier technologies. Much work is still needed to determine ways in which the advances in AI are similar or different from advances in other technologies in the past.

Given that generative AI tools can already mimic human creativity to an impressive extent, it seems inevitable that generative AI will be increasingly useful in creative jobs and industries, such as publishing, advertising, photography, film, music, television, cuisine, product design, app development, architecture, and live entertainment. Some creators are likely to develop sophisticated skillsets for using generative AI tools to boost the creativity or quality of their work, potentially gaining a significant competitive advantage over creators with weaker AI skills. In addition, many creators might lose their jobs as AI tools may be able to substitute for human labor in some cases. Organizations in creative domains may face important "make or buy" decisions regarding these new AI skillsets. Is creative human capital an important complementary asset for organizations? Should organizations invest in training employees to develop AI skills, or focus on recruiting and retaining creators who have demonstrated a capacity to acquire such skills on their own, or will third parties emerge that offer their creative skillsets on a contract basis?

Decades of research on creativity training programs suggests that individual creativity can be deliberately improved through formal skills training (Scott, Leritz, & Mumford, 2004). This evidence hints that AI skills training may be effective in creative domains if useful principles and practices can be codified and at least somewhat generalized. However, given the likely pace of change in AI technology, effective training programs may be difficult to design and keep up to date, especially in creative domains in which the state of art constantly changes even without the impact of AI (Jones et al., 2016). Scholars should have many promising opportunities to study how organizations navigate human capital challenges as new AI skillsets emerge and become sources of competitive advantage in such industries.

Building upon literature on dynamic capabilities by Teece et al. (2007), future research should explore whether and to what extent organizations are capable of updating complementary assets that allow them to take advantage of AI tools even as the technology develops rapidly. The notion of such "dynamic complementary assets" raises a number of questions for scholars to study, including how organizations can obtain the complementary assets they need and update these over time. The need to rapidly adjust a firm's stock of complementary assets also poses interesting implications for theories around "transaction cost economics" and the "boundaries of the firm."

Finally, we note that many of the questions we have posed are specific to the phenomenon of AI. However, we believe that these questions speak to broader theoretical issues. The phenomenon of AI provides an opportunity for scholars to study the boundary conditions of existing management and strategy literature. Importantly, the findings that emerge from these studies will also have practical implications that will be useful for managers and policymakers, including helping businesses determine which complementary assets are needed in order to create and capture value from AI.

CONCLUSION

The recent advances in AI tools, as exemplified by ChatGPT, highlight how quickly AI is advancing and thus how quickly AI may affect many facets of our economy and society. As researchers, we play an important role in understanding what AI is doing to organizations, managers, customers, and employees alike. We encourage researchers to step up to this challenge by addressing the questions we highlight here around the role of complementary assets for AI and the management of AI technology. Of course, our list of questions is far from exhaustive, and is meant to complement essays by other scholars that have outlined additional areas of inquiry into the role of AI in organizations (e.g., Amabile, 2020; Csaszar & Steinberger, 2022; Puranam, 2021; Raj & Seamans, 2019; Von Krogh, 2018). As consumers of research, we look forward to what we anticipate will be an abundant stream of research over the coming years around the role of AI in organizations, the economy, and society.

Author Information

Justin M. Berg is an Assistant Professor of Organizational Behavior at the Stanford Graduate School of Business. His research focuses on creativity and innovation. He studies how to successfully develop, evaluate, and implement creative ideas in and outside organizations. He received his PhD in management from the Wharton School of the University of Pennsylvania.

Manav Raj is an Assistant Professor of Management at the Wharton School of the University of Pennsylvania. His research studies are: a) how firms respond to innovation and technological change; and b) how institutional features and non-market forces affect innovation and entrepreneurship. He received his PhD from New York University's Stern School of Business.

Robert Seamans is an Associate Professor in the department of Management & Organizations at New York University's Stern School of Business, and Director of its Center for the Future of Management. His research focuses on how firms use technology in their strategic interactions with each other, and also focuses on the economic consequences of AI, robotics and other advanced technologies. He received his PhD from the Haas School of Business at UC Berkeley.

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Table 1: Top 20 Occupations and Industries Exposed to AI Language Modeling

Rank	Top 20 Occupations	Top 20 Industries
1	Telemarketers	Legal Services
2	English Language and Literature Teachers, Postsecondary	Securities, Commodity Contracts, and Other Financial Investments and Related Activities
3	Foreign Language and Literature Teachers, Postsecondary	Agencies, Brokerages, and Other Insurance Related Activities
4	History Teachers, Postsecondary	Insurance and Employee Benefit Funds
5	Law Teachers, Postsecondary	Nondepository Credit Intermediation
6	Philosophy and Religion Teachers, Postsecondary	Agents and Managers for Artists, Athletes, Entertainers, and Other Public Figures
7	Sociology Teachers, Postsecondary	Insurance Carriers
8	Political Science Teachers, Postsecondary	Other Investment Pools and Funds
9	Criminal Justice and Law Enforcement Teachers, Postsecondary	Accounting, Tax Preparation, Bookkeeping, and Payroll Services
10	Sociologists	Business Support Services
11	Social Work Teachers, Postsecondary	Software Publishers
12	Psychology Teachers, Postsecondary	Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)
13	Communications Teachers, Postsecondary	Business Schools and Computer and Management Training
14	Political Scientists	Credit Intermediation and Related Activities (5221 And 5223 only)
15	Area, Ethnic, and Cultural Studies Teachers, Postsecondary	Grantmaking and Giving Services
16	Arbitrators, Mediators, and Conciliators	Travel Arrangement and Reservation Services
17	Judges, Magistrate Judges, and Magistrates	Junior Colleges
18	Geography Teachers, Postsecondary	Computer Systems Design and Related Services
19	Library Science Teachers, Postsecondary	Management, Scientific, and Technical Consulting Services
20	Clinical, Counseling, and School Psychologists	Other Information Services

Notes: This table displays the top 20 occupations and top 20 industries exposed to advances in AI language modeling. The results come from Tables 1 and 2 of Felten et al. (2023).