# Riding the Generative AI Wave: A Research Agenda for Navigating Tensions and Generating Value

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## Abstract

*This paper sets out to explore the novel challenges and opportunities for value creation from Generative Artificial Intelligence (GenAI) and identify promising pathways for future research that can deeply inform practice. Drawing on insights from data executives globally and a case study, the research identifies three key emerging themes as crucial for understanding GenAI value: provider-driven model building and ownership, democratization of innovation and development, and localized model validation and application. These themes shed light on three set of tensions (need for speed versus transparency, democratizing innovation versus controlling risks, and automation efficiency versus knowledge preservation) that must be explored and resolved before business leaders can effectively advance their GenAI initiatives and find a path to value. Our proposed agenda addresses these tensions and aims to expedite socio-technical research regarding GenAI to keep pace with its rapid adoption.*

**Keywords:** Generative AI, Value Creation, Practice-based Research, Research Agenda.

## 1. Introduction

The emergence of Generative Artificial Intelligence (GenAI) has marked a turning point in the development of intelligent technologies. What distinguishes GenAI from its predecessors, such as machine learning, is its unique capacity to autonomously generate content across a spectrum of mediums, including text, images, and audio (Feuerriegel et al., 2023). This transformative capability not only promises to revolutionize the way routine work is performed but also the creative, difficult-to-codify tasks of specialists and knowledge workers (Benbya et al., 2023). GenAI can create slides, craft marketing campaigns, analyze legal documents, develop dashboards, write code and test software.

GenAI stands out as one of the fastest-adopted technologies in recent times. OpenAI's daily traffic to ChatGPT reached 100 million website visits in May 2024 following the GPT-4o announcement (Ver Meer, 2024). The technology's user-friendly nature and accessibility have contributed to its rapid consumability by users (from novices to experts) and its integration into a wide range of applications. Early evidence shows signs of GenAI impacting worker productivity, sparking speculation about its disruptive influence on labor markets (Eloundou et al., 2023). According to projections by Goldman Sachs (2023), the integration of GenAI could catalyze a 7% expansion in the global gross domestic product (GDP) over the next decade, accompanied by the displacement of approximately 300 million knowledge worker jobs. GenAI is projected to add up to $4.4 trillion to the global economy annually by automating tasks (McKinsey, 2023).

Despite GenAI's promising economic prospects, critical questions loom regarding its implications for organizations. The technology offers numerous opportunities, but it also raises significant challenges. These include biases (Ganguli et al., 2023), ethical and legal risks, violation of copyright laws (Smits & Borghuis, 2022), loss of privacy, fraudulent transactions and spreading content that are non-factual and non-original (Dwivedi et al., 2023; Benbya et al., 2023). Moreover, the technology may pose risks that are both unprecedented and unanticipated (Zuboff 2019). Therefore, there is an urgent need for practice-based IS research to advance our understanding of GenAI value creation (as opposed to value destruction) at the pace matching the rapid technological progression to unravel

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new socio-technical dynamics at play. This motivated us to ask the following research question:

*How does GenAI create value differently from traditional AI, and what specific research propositions can guide practice-based IS research to deeply inform how organizations can leverage this unique technology for value creation?*

In this paper, our aim is to connect with and stimulate the scholarly conversation on GenAI value. We embark on this journey by examining the established value creation processes of traditional AI and then contrasting it with an emergent understanding of GenAI value creation processes. To empirically investigate our research question, we conducted discussions with data leaders from around the world and undertook a case study at a large, global information business firm. Our analysis identified three key themes related to GenAI value creation that distinguish it from value creation associated with traditional AI, highlighting pressing tensions which must be explored and understood to effectively and responsibly create value from GenAI. We incorporate these tensions into a set of research propositions and urge leaders and researchers to act on them.

## 2. Research Background

### 2.1. GenAI versus Traditional AI

The field of managing AI (Berente et al., 2021; Baird 2021) has seen a surge in recent years, fueled by advancements in machine learning algorithms, which we consider as traditional AI (for example, supervised learning algorithms). This wave of intelligent technologies introduced technology characteristics that made their management unlike older data-driven and decision support systems. These facets included greater autonomy, self-learning and inscrutability (Berente et al., 2021; Someh 2022). While research in managing machine learning-driven AI technologies is still evolving, GenAI has taken center stage, becoming the technological frontier and bringing new opportunities and challenges at an unprecedented speed.

GenAI is qualitatively different from traditional machine learning-driven AI due to its ability to generate entirely new content (Feuerriegel et al., 2023). To enrich our understanding of these distinctions, we compare and contrast GenAI and traditional AI across three key dimensions: *input data*, *training process*, and *model outputs*. By examining these aspects, we can gain a deeper understanding of how GenAI operates and how it deviates from traditional machine learning techniques, and how its value creation might unfold.

**Input data** used for training GenAI models is massive in scale, including nearly everything available on the web (e.g., unstructured data from millions to billions of documents from websites, books, articles, and various types of media) (Dwivedi et al., 2023; Hacker et al., 2023). Traditional AI, however, mainly relies on domain-specific datasets (Feuerriegel et al., 2023). Such datasets include structured and unstructured data from databases, sensory devices, images, audio files, and social media (Grover et al., 2023).

GenAI's **training process** occurs through an unsupervised approach that builds large language models (LLMs) (Gupta et al., 2024). The models rely on a transformer architecture to capture dependencies (Dwivedi et al., 2023) between words and predict the next word in a sequence. LLMs can be fine-tuned by further training using labeled data or through utilization of Retrieval Augmented Generation (RAG). RAG uses a retrieval mechanism to fetch contextual information from an external source and ground the model's outputs based on the user's prompt (Dwivedi et al., 2023; Feuerriegel et al., 2023). Traditional machine learning is based on supervised or unsupervised techniques (Hacker et al., 2023). Supervised learning occurs by providing the algorithm with ground truth data, and the unsupervised learning involves exploratory techniques such as clustering (Duan et al., 2019).

In terms of **model output**, both GenAI and traditional AI produce outputs are probabilistic in nature (Bender et al., 2021; Feuerriegel et al., 2023). Their point of difference is in how the outputs are validated. For GenAI models, validation of outputs is qualitative and flexible (Dwivedi et al., 2023). These models generate text or other types of media, and evaluating their accuracy and quality requires human judgment and criteria, which may vary depending on context, application, and user preferences. For traditional AI, the validation of outputs is more quantitative and objective and typically occurs by using metrics that compare the model's predictions (Hacker et al., 2023) against ground truth labels. Traditional AI models are typically validated by cross-disciplinary teams of data scientists and domain experts; whereas, GenAI validation responsibility often falls to end-users.

### 2.2. Creating Value with GenAI

Figure 1 presents the AI Value Framework developed for traditional AI (Someh et al., 2020), providing a process-oriented view of how AI generates value for organizations. The framework outlines four core elements essential to understanding the value creation process: (1) At the project level, organizations create AI value by defining a business purpose, extracting meaningful insights from data, taking actions based on these insights, and ultimately realizing project value, (2) three key AI organizational resources—data, platform, and talent—enable the project, (3) three complementary organizational resources—leadership, domain knowledge, and governance—support and enhance the project's success, and (4) the aggregation of value from multiple AI projects contributes to organizational value.

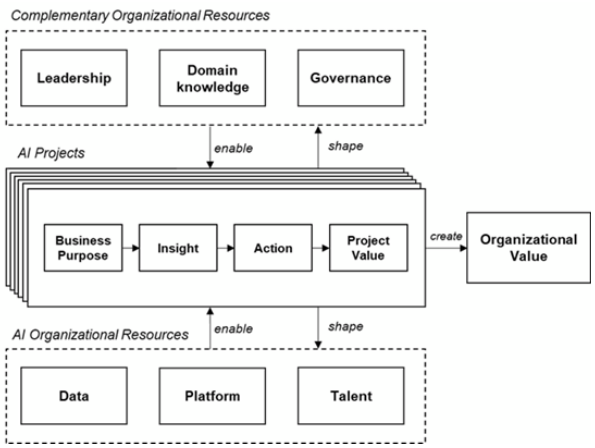


**Figure 1: A Process Model on AI Value Creation (Source: Someh et al. 2020)**

This framework emerged from an executive discussion and several case vignettes focused on traditional AI. However, as organizations increasingly adopt GenAI, it is essential to understand whether this AI framework and its components apply to GenAI and, if so, how and what adaptations are necessary. By revisiting the framework, we aim to develop a nuanced understanding of GenAI's value creation dynamics by carefully considering its unique characteristics, challenges, and opportunities.

# 3. Research Method

## 3.1. Executive Discussion

To validate the relevance of the AI value framework for GenAI technologies, we convened two online discussions on Slack with a research advisory board hosted by a north American academic research center in Quarter 4 of 2023 and Quarter 1 of 2024. The board consisted of 103 executives representing 61 large companies headquartered around the globe. Most organizations were multi-national and for-profit, and the executives held chief data officer, chief data architect, chief AI officer, or equivalent roles.

Each executive was asked to answer the following questions:

***Quarter 4 of 2023 Discussion Questions:***

1. *Is GenAI helping 1 advance your organization in the same direction, but faster; 2 lead your organization in completely new directions; or 3 misdirect focus?*
2. *What is the most promising in-process or deployed value-generating use case? Is it yielding expected returns?*
3. *How has generative AI influenced your organization's investments and capability building? What management practice or principle will be critical for making the most from generative AI specifically?*

***Quarter 1 of 2024 Discussion Questions:***

4. *By your estimate, what percentage of employees in your organization currently collaborates with (generative) AI in their day-to-day tasks? What do you expect this percentage to be in 2027?*
5. *What new roles or required skills and capabilities are emerging because of increased employee collaboration with (generative) AI solutions?*
6. *Could you share an example of a particularly innovative (or perhaps unexpected) way in which employees have collaborated with AI solutions in your organization?*

In our Q4 2023 discussion, 35 executives from 34 organizations answered our questions, and 33 executives from 32 organizations answered our questions from Q1 2024. Ultimately, 52 executives from 47 organizations participated across the two online discussions, resulting in a 77 percent response rate. Several respondents provided artifacts (e.g., internal company reports, decks) to support their answers.

To analyze the data collected from executives, we employed the Gioia Method (Gioia et al., 2013). Initially, we developed first-order categories inductively to organize the data, closely adhering to participants' terms and language to preserve their intended meaning. We then grouped the first-order categories and put a researcher lens on to abstract the first-order categories to create themes. In our findings section, we present the three themes we identified, along with first-order categories and key excerpts from data as evidence supporting the themes.

## 3.2. Case Study

To validate the themes on GenAI value and understand how they manifest in an organizational setting, we employed a single case study research approach. Case studies are valuable for investigating contemporary phenomena within their organizational context, providing rich and detailed descriptions of how and why outcomes occur (Yin, 2009). Single case studies are appropriate when the case is unique or can validate evidence from other sources (Yin, 2009). Drawing on the case study helped the research team to explore actual GenAI initiatives within a large multinational information services firm that provides expert solutions, software, and services in various industries (InfoCo). The case study reported in this paper is revelatory, as the case organization employed several innovative ways to embark on GenAI initiatives and reported early evidence of achieving value from those initiatives.

InfoCo has approximately 20,000 employees worldwide, serving customers in dozens of countries. Data collection consisted of two research team members who conducted 21 semi-structured interviews during the fall of 2023 and the first two quarters of 2024.. In 2023, the interviews were conducted in a hybrid manner whereby one interviewer was on-site at the company headquarters while the second interviewer participated by Zoom. In 2024, all interviews occurred virtually. The final six interviews in 2024 focused on questions specific to GenAI. The research team also gathered publicly available material about GenAI use at the organization.

The case study data analysis was focused on validating the themes that emerged in the previous phase to shed light on how the themes might manifest in an organizational setting.

# 4. Findings

## 4.1. Emerging Themes from Executive Discussion

Drawing on key differences between GenAI and traditional AI techniques, the research team engaged in a process of iterative coding and discourse to select the top three themes that had potential for significantly changing organizational dynamics associated with the AI value framework.

**Theme 1: GenAI Provider-based Model Building and Ownership**

Based on the executive discussions, the research team identified three first-order categories that informed a theme of GenAI Provider-based Model Building and Ownership: speeding up time to market, accepting provider offerings, and Managing data sources (see Table 1, which includes sample evidence).

GenAI models are largely owned and controlled by the organizations that develop and train them. Provider-based GenAI offerings can benefit user organizations by eliminating investments associated with AI model building and by making available better and more models for organizational value creation. However, GenAI provider organizations often retain rights over model mechanics and determine the way in which their model will be distributed (such as via APIs), how the models can be used (such as for academic purposes), and how the model will be monetized (such as via a paid subscription service). As such, the users of GenAI provider models are limited in what they know (or can discover) about a model and constrained in how to apply a model for specific use. Such power dynamics can pose challenges for user organizations, such as high uncertainty up-front regarding the value proposition of a GenAI provider's model. User organizations need to navigate contractual agreements by GenAI providers that impose long-term or undesirable commitments on the users of their models, opaque practices that need to be understood as a part of AI capability and trust building, and data sourcing and sharing strategies.

**Table 1: Theme 1 Categories and Evidence**

| **Theme 1: GenAI Provider-based Model Building and Ownership** |
|---|
| **Speeding up Time to Market**<br>*"We are seeing more vertically integrated vendor stacks. All the at-scale vendors offer pre-integrated, managed AI platforms... We see the opportunity for AI to drive and accelerate… through much faster time to market for AI capabilities."* |
| **Accepting Provider Offerings**<br>*"We've launched a 'vendor defense council' around AI, so we can evaluate them from the ground up to see the potential impact of [data] leakages and things ending up where they weren't intended to."*<br>*"Public generative AI continues to be locked down. Public LLMs are blocked. We have not settled on approaches for creating/managing/using LLMs."* |
| **Managing Data Sources**<br>*"[We are] focused on data input and output risks. Specifically, we are conscious of any inputs that could be used to retrain our models and outputs that could expose sensitive data or harm our corporate reputation."* |

**Theme 2: Democratized Innovation and Development**

Based on the executive discussions, the research team identified three first-order categories that informed a second theme of Democratized Innovation and Development: focusing organizational attention, controlling widespread engagement, and rethinking knowledge management (see Table 2, which includes sample evidence).

**Table 2: Theme 2 Categories and Evidence**

| **Theme 2: Democratized Innovation and Development** |
|---|
| **Focusing organizational attention**<br>*"Senior leadership has been so enamored with early use cases that they have lost sight of them being one of hundreds, likely thousands of use cases, and perhaps not always the most important ones. Certainly not all of what we should be running at right now."*<br>*"GenAI and related LLMs are much easier for the masses to understand and therefore ideate. The risk is a laundry list mentality and [investments in] areas that are not business critical to solve or yield limited to no real business benefits."*<br>*"We launched an enterprise GenAI program to focus on seven specific golden use cases that we identified as the most beneficial for the company…"* |
| **Controlling Widespread Engagement**<br>*"The whole company received early generative AI training."*<br>*"From a governance perspective, we have issued guidance to all employees on the appropriate use of generative AI and have classified the use into "Areas that are always ok," "Areas that are never ok," and "Areas you need to check with our AI Task Force on to gain approval."* |
| **Rethinking Knowledge Management**<br>*"We are using LLM to load in our own Knowledge Management Data to create a more natural language style search to help individuals have access to corporate knowledge."*<br>*"Our first foray will be in knowledge summarization for our customer-facing staff, helping them navigate more seamlessly through our extensive knowledge base of policies and procedures."* |

The combination of market attention on GenAI tools and GenAI consumerization have led to mass GenAI interest and adoption by senior executives through to front-line workers. For one, the market hype and competitive fears of being left behind are creating a sense of urgency which is pushing leaders to make GenAI investments. At the same time, individuals can access a host of GenAI tools, many of which are no or low cost, easy to use, in-use by peers, and relevant for current task needs. Additionally, software vendors increasingly are embedding GenAI into preexisting enterprise and consumer software products. Because of the resulting explosion of employee interest and engagement, GenAI use cases are mushrooming in organizations, prompting leaders to discover ways to focus organizational attention on ideas that promise the greatest value creation given the organization's business model and strategic intent. At the same time, organizations are trying to manage widespread participation in innovation and development activities and identify how to craft knowledge management strategies that incorporate GenAI-enabled ways to identify, curate, and access organizational expertise.

**Theme 3: Localized Model Validation and Application**

Based on the executive discussions, the research team identified three first-order categories that informed a third theme of Localized Model Application: allocating work to machines, locally verifying model results, and locally adapting model output (see Table 3, which includes sample evidence).

**Table 3: Theme 3 Categories and Evidence**

| **Theme 3: Localized Model Validation and Application** |
|---|
| **Allocating work to machines**<br>*[We need] some level of governance that does not stifle innovation yet ensures that generative AI augments but does not make decisions that must be made/confirmed by a [worker].*<br>*"How to rethink the business model and business processes, rather than bolting a chatbot onto an existing process and expecting magical outcomes?"*<br>*"Some of the best examples have come from people experimenting with LLMs and making them apply to their work, in a way that we would struggle to coordinate centrally."* |
| **Locally verifying model results**<br>*"More can be automated, but people are required to make sure that there are no hallucinations."*<br>*"Everyone needs to get better at critical thinking and generally being skeptical."*<br>*"We are seeing an increasing need for individuals to thoroughly validate the response of models anytime the knowledge graph changes (new release or finetuning of a model)."* |
| **Locally adapting model output**<br>*"We are seeing a significant uplift in the need for prompt engineering to ensure that users are receiving the output they expect from the generative AI solution."*<br>*"We enabled Microsoft copilot and are doing a major campaign to get everyone to practice their prompting skills."* |

GenAI users wear many hats, including developers, validators, and work designers as they dynamically use and adapt GenAI tools for their tasks needs. To effectively use GenAI, however, users need new skills associated with the new roles, such as prompting to adapt model output, model validation to verify model results amidst hallucination, and GenAI literacy to understand the potential and limitations of the technology. The GenAI user thus represents a key multi-faceted new role – and one held by potentially a huge number of employees – for organizations to develop, manage and exploit to ensure fruitful GenAI applications. Further, when organizations succeed in developing GenAI users, they set up the chance for individual workers to mold and shape GenAI to become a useful and reliable "co-worker" and to optimally allocate work to machines.

## 4.2. Case Study Insights

InfoCo is a large, global information business firm that transformed in the past decade from a printing company to a company that provided informational solutions to businesses. The company managed large amounts of information and competed on delivering high quality subject matter expertise and workflow management. The company had been investing in contemporary people, process and technology and established capabilities in data science, including predictive AI.

In recent years, the company began experimenting with GenAI, and according to a data science leader, "Generative AI took all of us by storm. We really felt *this is different*. We did a two-week hackathon, taking our existing AI use cases and applying this technology to get an early read. And we were pleasantly surprised with the accuracy levels, the recall, the precision levels… We said, "Wow, the traditional way of working, where we will train the model, we have multiple iterations, and then we will get there. This is not the same."

InfoCo leveraged existing vendor partnerships to access, learn and quickly develop GenAI applications. The company ensured that their GenAI technology providers could not leak the company's information because of GenAI use. The company's first step was to create secure environments and work with partners to make sure their data sets were secure. One leader explained, "Our curated data is what makes us valuable. There's a risk if our curated data goes out. That's why there's all those boundaries about everything." Another leader explained that vendor lock-in also was a concern. "We are picking the right partners [to give us] scale and standardization and protection. But at the same time [we are] remaining nimble and open as [other vendors come on board with new, better offerings]."

There was a lot of interest across the enterprise in GenAI. Senior leaders worked to give employees a safe and responsible way for experimenting. One leader explained, "We don't want people to start spinning up their own GPTs. But we couldn't pass a mandate for people to not use ChatGPT. Banning won't work, in my experience." Instead, InfoCo incorporated GenAI support and funding into its existing innovation processes, which included an annual hackathon. They encouraged employees to submit GenAI-based hackathon ideas (about 40% of hackathon teams did so), but then assigned a GenAI advisor to those teams "so we had a controlled way of doing this." Another leader described a challenge in ensuring the right ideas moved forward with funding: "The challenge really is the quantification of the idea, the return on investment and business impact. There are just so many ideas, but what are the precious few that will really move the business forward?"

Over time, GenAI applications began emerging across the company. In one case, the sales area was inundated with customer questions regarding a new product. The sales team, many of whom were new employees, could not keep up with the volumes of inquiries. The product owner proposed a GenAI-driven chat bot to enable sales employees, and the data science team built one quickly. At first, there was an initial uptick on the chat bot, but people went back to former work habits. In the second iteration, the chat bot was embedded into product support processes.

In a different part of the company, a group wrote summaries of bills and regulations. A data scientist created an assistant tool to generate first-draft summaries, based on internal data sources, for his colleagues to review. Initially, there were variances that the group fixed, and over a couple of months and four iterations, they adjusted the data sources used and the process until the quality measures met requirements – up to 90% accuracy.

Finally, in a third part of the company, process leaders proposed a use case to replace a historically manual task. GenAI would extract information from a large document and create an abstract of key topics. Early experiments produced high quality output; however, occasionally GenAI generated false content. The group is determining how to manage its workflow effectively in which the language models are applied at the right stage, using workers as both fact-checkers and quality control.

InfoCo expected that GenAI would influence the nature of work at the company and to prepare, leaders educated employees about the power of GenAI tools and dissected core workflows into smaller chunks to identify where GenAI could add value and where human expertise was needed. Leaders viewed employee involvement as key for managing hallucinations and the probabilistic nature of GenAI tools.

In 2024, InfoCo leaders viewed GenAI as an important and promising tool for creating business value: "this new power tool of generative AI will have deep impact in a relatively short order." But there was still a lot to learn about how to manage the technology. According to one leader, some employees were "coming up with all kinds of new ways of thinking about our work process. So, what we realized is that while democratization is a good thing, we need to figure out how to harness this energy into a program and a process."

## 5. Proposed Research Agenda

The themes that emerged from our data analysis point to three key sets of tensions that business leaders are facing in relation to value creation from GenAI. These tensions include (1) need for speed versus transparency, (2) democratizing innovation versus risk control, and (3) automation efficiency versus knowledge preservation.

### 5.1. The Tension of Need for Speed Versus Transparency

The accessibility and consumability GenAI have fueled rapid adoption, sparking fierce competition among provider organizations and heavy investments in GenAI by user organizations. In this fast-paced environment, provider-based models are highly attractive due to promise of quick deployment and faster time to market. However, this advantage comes with drawbacks, rooted in a lack of transparency regarding model mechanics and data sourcing and management processes, the latter which impacts the ease of IP management. Our insights suggests that future GenAI value creation needs to navigate the tension between the need for speed versus transparency requirements. In essence, future practice-based research should help leaders effectively manage the tension of optimizing both for speed-to-market and responsible value creation. Hence, we propose:

*P1: GenAI research is required to understand how GenAI user organizations can understand, evaluate, and remediate intellectual property and data provenance concerns in ways that allow them to expeditiously leverage provider-based GenAI models.*

*P2: GenAI research is required to understand how GenAI user organizations can justify model output in ways that allow them to expeditiously leverage provider-based GenAI models.*

### 5.2. The Tension of Democratizing Innovation Versus Controlling Risk

GenAI value research involves a second critical tension that needs to be resolved: democratizing innovation versus controlling risk. This tension stems from the democratization of GenAI-powered solution development and its accessibility to many individual employees. Our findings identified that GenAI innovation can occur outside of traditional R&D structures, which historically support centralized, controlled innovation activities. GenAI introduces a new territory for organizations in which every employee can participate in GenAI-powered innovation and solution development. As such, leaders need to understand how to manage such widespread innovation activities in ways that properly identify and mitigate emerging and unprecedented risks and avoid negative consequences. Hence, we propose:

*P3: GenAI research is required to understand how organizations can enable and guide widespread GenAI--powered innovation activities so that the organization can achieve desired GenAI outcomes.*

*P4: GenAI research is required to understand how to establish and maintain appropriate governance and controls while simultaneously democratizing GenAI-powered innovation.*

### 5.3. The Tension of Automation Efficiency Versus Knowledge Preservation

Using GenAI over time may have a hidden cost for organizations: organizational knowledge loss. Over time, excessive reliance on AI can create a dangerous phenomenon – automation complacency (Rinta-Kahila et al., 2023). Domain experts, reassured by initial successes with verifying model outputs, gradually lose the ability to scrutinize model calculations and validate outputs. This complacency can morph into a full dependence on AI, effectively removing humans from the loop. The consequences include relying on fully automated solutions, which increases efficiencies as well as job displacement and the erosion of vital organizational knowledge and employee expertise. This raises a critical question: how can organizational leaders navigate the tension of automation efficiency versus knowledge preservation, so that they can develop strategies to take advantage of both sides: achieving automation efficiencies while also managing to maintain and develop organizational knowledge and preventing skill erosion in their domain experts. In doing so, there will be a need to for organizations to develop an understanding of how various domains will change to incorporate GenAI capabilities.

*P5: GenAI research is required to understand how organizations effectively manage, cultivate, and expand their knowledge base over time., while preventing knowledge loss from reliance on GenAI over time.*

*P6: GenAI Research is needed to explore how organizations can build and retain employee expertise and prevent skills erosion from GenAI use over time.*

## 6. Discussion

GenAI's unique characteristics present both challenges and opportunities, and potentially alter components and/or dynamics of the Process Model on AI Value Creation as depicted in Figure 1. We offer three examples. First it might be necessary to include "Partnering Capability" as an additional complementary organizational resource. Provider-based GenAI offerings can eliminate the need for significant investments in AI model building and provide access to superior approaches to AI value creation; however, such offerings happen within a context of organizational GenAI provider and user relationship. Likely, the partnering literature, and the incorporation of the partnering capability in GenAI research, will be helpful for understanding GenAI value creation. A second example: how does knowledge influence – and get influenced by – AI value creation? As the building, curating, accessing, use and retention of knowledge grows in importance along with the growth of GenAI activity, researchers may want to view and explore knowledge as an organizational resource to explore. Third, drawing on critical differences between GenAI and traditional AI techniques (Hacker et al., 2023), our findings indicate that the AI Value Creation framework may require a lower level of granularity, moving from an AI project-level accumulation of benefits to individual application-level benefits accumulation.

This paper has two key implications for readers to consider. First, navigating GenAI adoption involves managing a distinct AI phenomenon that requires new and changed practices associated with AI Value Creation. Second, creating value using GenAI requires that leaders manage three tensions: need for speed versus transparency, democratizing innovation versus controlling risks, and automation efficiency versus knowledge preservation; recognizing and addressing these tensions will be key for organizations intending to fully leverage GenAI opportunities.

This paper offers a practice-based research agenda. We provide a summary of our practice-based research propositions in Table 4. We encourage researchers to adopt creative and innovative approaches to refine and explore the framework and research propositions to generate relevant managerial insights. For example, researchers could employ social network analysis or configurational research approaches to better understand distributed, widespread GenAI innovation and development processes; or, they could conduct longitudinal studies to explore how organizations can maintain expertise and prevent skills erosion with increasing GenAI adoption.

**Table 4: Summary of Research Propositions**

| **Emerging GenAI Value Themes and Associated Tensions and Research Propositions** |
| --- |
| **Theme 1: GenAI Provider-based Model Building and Ownership**<br>**Tension 1: Need for Speed Versus Transparency**<br>***Research Propositions:***<br>• ***P1***: *GenAI research is required to understand how GenAI user organizations can understand, evaluate, and remediate intellectual property and data provenance concerns in ways that allow them to expeditiously leverage provider-based GenAI models.*<br>• ***P2***: *GenAI research is required to understand how GenAI user organizations can justify model output in ways that allow them to expeditiously leverage provider-based GenAI models.* |
| **Theme 2: Democratized Development and Use**<br>**Tension 2: Democratizing Innovation Versus Controlling Risk**<br>***Research Propositions:***<br>• ***P3***: *GenAI research is required to understand how organizations can enable and guide widespread GenAI--powered innovation activities so that the organization can achieve desired GenAI outcomes.*<br>• ***P4***: *GenAI research is required to understand how to establish and maintain appropriate governance and controls while simultaneously democratizing GenAI-powered innovation.* |
| **Theme 3: Localized model validation and application**<br>**Tension 3: Automation Efficiency Versus Knowledge Preservation**<br>***Research Propositions:***<br>• ***P5***: *GenAI research is required to understand how organizations effectively manage, cultivate, and expand their knowledge base over time., while preventing knowledge loss from reliance on GenAI over time.*<br>• ***P6***: *GenAI Research is needed to explore how organizations can build and retain employee expertise and prevent skills erosion from GenAI use over time.* |

## 7. Conclusion

GenAI is a top priority for business leaders, offering significant potential for AI value creation. However, without proper management, GenAI can pose substantial risks to organizations. Our conversations with executives identified three key themes regarding GenAI's distinctiveness: GenAI Provider-based Model Building and Ownership, Democratized Development and Use, and Localized (distributed, decentralized) Model Validation and Application. The themes were explored within an organization currently managing GenAI adoption, and ultimately, our analysis revealed three tensions that business leaders must manage to create value from GenAI. These tensions require thorough exploration by academics to help practitioners effectively navigate and advance their GenAI initiatives. Our proposed agenda addresses these tensions and aims to expedite socio-technical research into GenAI to keep pace with its rapid adoption.

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