evolution ltd

Research Paper

September 30, 2024

Working Paper — v24

How Disruptive Will Generative AI Be?

A Micro-Level Analysis of Evidence and Expectations

Michael G Jacobides, London Business School and Evolution Ltd, mjacobides@london.edu

M. Dalbert Ma, London Business School and Evolution Ltd, dma@london.edu

Michael G Jacobides (mjacobides@london.edu) is the Sir Donald Gordon Professor of Entrepreneurship & Innovation and Professor of Strategy at London Business School, and Evolution Ltd's Lead Advisor. He is Academic Advisor to BCG's Henderson Institute, member of the World Economic Forum's AI Governance Alliance, co-author of its White Paper on platforms and ecosystems, and ranked as one of the 50 top management thinkers. **M. Dalbert Ma** (dma@london.edu) is a PhD candidate in Strategy & Entrepreneurship at London Business School, and has worked as an Analyst in Evolution Ltd. He holds a BA in Philosophy, Politics and Economics from the University of York, an LLM in Intellectual Property and Competition Law from Erasmus University Rotterdam, and a Master in Management from IESE Business School.

The research team was supported by **Yuri Romanenkov**, Senior Advisor at Evolution Ltd and Programme Director for Next Generation Digital Strategies at London Business School, **Justinas Sukys**, Advisor at Evolution Ltd, as well as **Chinmay Bajpai, Netra Hirani, Yiru Susan Wang** (research) and **Tom Albrighton** (copy-editing).

Executive Summary

- Generative AI (GenAI) has provoked both hype and intense debate in the business world. Many leading consultants, academics, and industry experts are heralding it as a transformative force for both organizations and entire sectors, with some even projecting trillions in potential economic impact. A minority of academics, however, argue that the impact will be more modest in economic terms and will depend on complementary investments.
- Whatever the size or speed of GenAI's impact, the question remains: how disruptive will it truly be? Most research predicting major change has focused on simple, modular, individual tasks—yet such capabilities may not necessarily aggregate to organizational or sectoral levels, especially when we consider the historical precedent of earlier technological shifts.
- Our comprehensive study gathered valuable insights into strategic decision-making and resource allocation in the context of GenAI adoption. We employed a three-stage approach: initial qualitative roundtables with 96 executives, a quantitative survey of 217 executives, and a final qualitative stage involving 163 executives.
- Our findings reveal significant disparities in expectations of disruption, both between and within sectors, suggesting the potential for heterogenous effects. We also distinguish between GenAI-driven *displacement,* i.e. the wholesale challenge to value-add activities of firms and entire sectors, and its impact on supporting *differentiation* for firms leveraging GenAI. Some settings more exposed to GenAI will see both occur simultaneously.
- We found that industry-specific features play a key role in how executives view the threat of displacement from GenAI. For example, executives in heavily regulated industries or those requiring high output accuracy feel more protected. The forces driving displacement fears and differentiation opportunities sometimes overlap, suggesting that in certain sectors, GenAI might benefit some firms while challenging others.
- At the organizational level, executives see assets such as proprietary data and tacit knowledge as crucial for leveraging GenAI for competitive advantage, while organizational structure, particularly modularity, plays a key enabling role in deployment.
- Our findings suggest that organizations should develop capabilities in proprietary data, data cleanliness, organizational flexibility, and tacit knowledge to leverage GenAI effectively. Strategies should balance sector-specific dynamics with unique organizational capabilities.
- Policymakers need to consider frameworks for data democratization, sector-specific interventions, and broader analytical approaches to competition. These efforts should aim to promote equitable GenAI integration while addressing its wide-ranging implications on market dynamics and cross-sector disruption.
- Our research underscores the need to look beyond the hype surrounding GenAI and consider broader organizational and sectoral dynamics. This more nuanced approach reveals that GenAI's impact is likely to be uneven and context-dependent, challenging simplistic narratives of universal disruption or transformation.
- Our paper offers a rigorous basis for helping companies rethink their approach to GenAI, with more focused frameworks / tools for guiding strategy being developed by Evolution Ltd.

Acknowledgments

This study was made possible by a collaboration between the London Business School, the Institute of Directors in the UK (IoD) and Evolution Ltd, generously funded by the UK's Regional Innovation Fund. The original team of researchers included Yuri Romanenkov, Justinas Sukys, Chinmay Bajpai, Netra Hirani, Yiru Susan Wang supported by Tom Albrighton in copy-editing. Faisal Khan, Chair IoD South, and Chair, IoD Science, Innovation and Technology Expert Advisory Group provided valuable guidance and encouragement, as did Roger Barker, IoD's Head of Policy. Sasha Trapani, IoD Press and Policy Officer offered stellar support and engagement, and we are indebted to the IoD members who generously offered their time, and in particular this project's Advisory Board: Pauline Norstrom, Philippe Vogeleer, Samir Chekini, Sue Milton, Yvonne Whiteley, Alistair Elder, Angus Friday, Darren Rickards, David Stringer-Lamarre, Dianne Lee, Giles Ward, Ian Clements, Perminder Ghataore and Virginia Driver. Lord Clement-Jones, co-chair of the All-Party Political Group on AI, Lord Holmes, proposer of the Member's Bill on the UK AI Regulation Authority, and Viscount Camrose, Minister of State for AI in the UK are acknowledged for their comments on our Report. General Atlantic (especially Jesse Thomas, VP leading data science) have offered valuable guidance during our project of AI's impact on its portfolio that mirrored this study. We appreciate the comments and feedback from our presentation in Stanford's HAI / Digital Economy Lab, and our host Erik Brynjolfsson, as well as Kathy Eisenhardt, Angela Aristidou & Panos Adamopoulos-Moraris, the participants in the Berkeley Open Innovation Seminar and participants of two Academy of Management workshops on AI for comments and feedback. We are grateful for the detailed comments on our manuscript from our academic colleagues Ron Adner, Dan Cable, Raj Choudhary, Donal Crilly, Gary Dushnitsky, Kristina McElheran, Ioannis Ioannou, Do Yoon Kim, Arianna Marchetti, Ethan Mollick, Keyvan Vakili and BCG/BHI's David Zuluaga Martinez. We would also like to acknowledge Evolution Ltd and London Business School's Knowledge Exchange Fund for additional support.

Academic Abstract

This study examines executives' assessment of Generative AI's impact on competitive advantage and their expectations of its disruptive potential. Through abduction combining qualitative and quantitative work with UK Directors, we consider how executives view GenAI's impact as differing between and within industries and which organizational, technological and sectoral variables they perceive as most significant. We find that GenAI is seen as potentially causing sector-level displacement, especially in the presence of modularity and the absence of sector-level regulation. Executives anticipate enhancing differentiation through GenAI drawing on firm-level complementary assets, suggesting a source of incumbent resilience. We find that the more pattern recognition and proprietary data are important, the greater the perceived disruptive potential of GenAI, and the greater its perceived ability to drive displacement and differentiation alike.

Keywords: artificial intelligence, generative ai, strategy, competitive advantage, technological disruption, pattern recognition, modularity

Managerial Abstract

How disruptive will GenAI be? We find that shifting the focus from modular tasks (where GenAI can shine) to sectors and business models offers more caution and qualifications. We draw on qualitative and quantitative analysis of UK Directors' assessment and expectations on GenAI's disruptive potential, which varies across and within industries. We distinguish between expectations of *displacement threat* and hopes for AI-based *differentiation*, but find they co-vary. Executives perceive sector-level factors such as regulation and output accuracy requirements as buffers protecting them from displacement threat and new entry. Proprietary data and tacit knowledge are perceived as GenAI enablers in generating differentiation. This suggests that GenAI will not have a uniform effect across sectors or business models and will challenge average performers while benefiting well-prepared firms.

Note: Paper under review for academic journal

1. Introduction

The rapid advance of the capabilities of artificial intelligence (AI), particularly generative AI (GenAI), represents a crucial technological shift. AI has demonstrated superior performance in a range of complex tasks and functions previously thought to require human intelligence, including strategic games (Risi and Preuss, 2020), prediction (Agrawal, Gans, and Goldfarb, 2018; Cowgill and Tucker, 2020). GenAI in particular has advanced at a breathtaking speed, with demonstrable achievements that would be unthinkable even months ago (Csaszar, Ketkar, and Kim, 2024; Kim *et al.*, 2024), which go far beyond traditional pattern recognition to encompass creative writing (Doshi and Hauser, 2023; Noy and Zhang, 2023) or scientific problem-solving (Boiko, MacKnight, and Gomes, 2023; Ludwig and Mullainathan, 2023; Manning, Zhu, and Horton, 2024). This rapid progress has raised critical questions regarding the implications for organizations and competition (Brynjolfsson, Li, and Raymond, 2023; Csaszar and Steinberger, 2022; Dell'Acqua *et al.*, 2023; Girotra *et al.*, 2023; Otis *et al.*, 2024). GenAI's ability to manipulate and analyze data and build new content in unprecedented ways has the potential to reshape industries, redefine competitive advantage and transform the nature of work itself (Achiam *et al.*, 2024; Bubeck *et al.*, 2023; Girotra *et al.*, 2023; Wang *et al.*, 2024).

On the other hand, there are signs that rushing to assume that GenAI will have a profound effect because of its speed of development may lead us astray. First, systematic evidence indicates that AI adoption is limited to a small subset of leading firms (McElheran *et al.*, 2024), while GenAI utilization is mainly observed among high-performing individuals rather than at the organizational level (Humlum and Vestergaard, 2024; McKinsey & Co, 2024). Second, while researchers (Mollick, 2024) and consultants (McKinsey & Co, 2023) have been quick to enthuse about what GenAI can achieve, it may not be cost-effective to deploy it at scale (Svanberg *et al.*, 2024). Third, scholars of earlier general purpose technologies such as computers, electricity, or steam power note that they usually require significant changes in complementary assets, infrastructure and organization (Agrawal, Gans, and Goldfarb, 2021; Bresnahan, 2021, 2024; Bresnahan and Trajtenberg, 1995; David, 1990; Rosenberg, 1998).

AI has already shown that it can increase the asymmetry of benefits, and favor a few firms with a digital infrastructure (Iansiti and Lakhani, 2020; Jacobides, Brusoni, and Candelon, 2021). What should we expect from GenAI? Will it disrupt firms and sectors (Christensen, 1997), or prove to sustain industrial leadership (Henderson and Clark, 1990)? At the individual level, evidence is mixed. While several studies suggest it serves as an "equalizer" (Dell'Acqua *et al.*, 2023; Mollick, 2024), some indicate it may exacerbate existing skill disparities (Otis *et al.*, 2024). But what of organizations, their business models, and sectors where they compete? Will GenAI increase inequalities or attenuate them? And does the answer depend on other factors that combine with GenAI to tell us where we should expect significant impact and where not?

Definitive answers are hard to find, as we have yet to see empirical evidence on the impact of GenAI. Yet, the speed of technological development and the magnitude of investments and expectations oblige us to sift through whatever evidence we *do* have as best we can. Here, we present the results of a systematic, large-scale investigation of use patterns, satisfaction and, mostly, executive perceptions of use patterns, current impact, and expectations of change from GenAI. It is through the study of these executive perceptions that we can elucidate channels of resource allocation, aligning epistemologically with established research on the role of managerial perceptions in shaping organizational actions and outcomes (Eggers and Kaplan, 2009; Eggers and Park, 2018; Kaplan and Tripsas, 2008). As our respondents are members of Boards of Directors, we view their perceptions as particularly important, since, given the level of uncertainty, Board-level perceptions will determine corporate direction, investments and use of technology alike. Furthermore, our abductive approach does not focus on the validity of these perceptions, but rather on uncovering qualitative and quantitative patterns and causal pathways that explain why GenAI is perceived by executives to be more important in some contexts and less so in others.

As such, we consider what features account for perceptual *variance* between and within sectors, and what other factors co-determine whether GenAI is disruptive or not (Christensen, 1997; Christensen and Raynor, 2010). Specifically, we consider three questions: (1) *What impact has GenAI had and how does this differ across sectors?* (2) *What explains the variance in experiences across but also within sectors?* and (3) *What are the expectations in terms of GenAI's potentially disruptive impact, and what explains the variance in these expectations across and within sectors?* In so doing, we qualify disruption, by considering whether it relates to "displacement"- i.e., the wholesale bypassing of activities (e.g., in advisory and advertising) that used to be performed by incumbents, and differentiation on the basis of GenAI.

This study drew on an innovative collaboration between the Institute of Directors (IoD), the UK's largest organization for director-level executives, and a leading business school, supported by a research team funded by the UK's Regional Innovation Fund. We employed a mixed-methods, abductive approach in three stages (Mitchell *et al.*, 2022; Timmermans and Tavory, 2012). Initial roundtables involved 96 executives to scope key variables and attributes (Furnari *et al.*, 2021). These insights informed a survey of 217 IoD members, revealing empirical patterns among variables of interest. Finally, we conducted nine targeted roundtables comprising 163 executives, structured to test the robustness of variable relationships. Participants were selected based on survey responses and grouped by specific characteristics (e.g., high vs. low proprietary data importance). This approach, inspired by Mitchell *et al*. (2022), allowed us to mechanically tease out differences by exposing similar groups to identical stimuli and questions. Our method proved effective in capturing heterogeneity within and across sectors for a technology that so far lacks a dominant design or "killer use case" (Abernathy and Clark, 1985; Anderson and Tushman, 1990). It enabled us to gather nuanced perspectives from executives facing similar industry challenges but with potentially divergent experiences and expectations of GenAI.

Our study reveals insights that qualify and extend existing work, which either looks at macro-level adoption statistics (McElheran *et al.*, 2024) or, more often, focuses on potential benefits of GenAI at the level of a specific task (Boussioux *et al.*, 2024; Brand, Israeli, and Ngwe, 2023; Brynjolfsson *et al.*, 2023; Dell'Acqua *et al.*, 2023; Noy and Zhang, 2023)—approaches that may yield impressive if non-generalizable results to the organizational and competitive context. Instead, ours is the first large-scale study we are aware of that considers how executives perceive GenAI to affect different sectoral, business-model, or organizational contexts.

In particular, with the reservation that our findings rely on executive *expectations* of change (albeit without the issues of post-facto attribution bias), we find significant variance in the extent to which GenAI is expected to disrupt. We further decompose such anticipated disruption by looking at the risk of *displacement,* such that GenAI takes over part of the value-add in a sector (as it does in parts of communications or legal research services), and GenAI's perceived ability to confer advantage through renewed *differentiation* for well-positioned firms. We further find that the concern about displacement differs primarily between sectors, with factors such as the reliance on technical knowledge and the role of sector-level regulation shaping executives' views on their vulnerability to GenAI displacement, whatever the use cases may be.

Second, we find that modular settings are more likely to be affected by GenAI, while at the same time, regulation and organization limit such modularity, suggesting that we may want to be cautious in extrapolating the benefits of GenAI demonstrated for specific, modular tasks. That said, there is optimism about the ability to create unique differentiation through GenAI, even though executives disagree on which complementary assets will be crucial even within the same sector, other than pattern recognition and the importance of proprietary data. Taken together, our findings suggest both an uneven application of GenAI and the potential for significant redistribution of competitive advantage, with potential saving graces for incumbents.

Our findings shed light on the nature of GenAI's expected impact, and more broadly help us rethink the nature of technological disruption. We find that the current task-level focus on GenAI should be complemented by the analysis of sectoral and firm-level value propositions and business models. In this regard, we find that GenAI is likely to affect disruption via displacement and differentiation alike. This dual nature of GenAI as both competence-enhancing and competence-destroying may have major implications for the competitive landscape (Csaszar *et al.*, 2024; Krakowski, Luger, and Raisch, 2023; Lechner *et al.*, 2024; Raisch and Krakowski, 2021).

While novel GenAI technologies are generally developed by a small number of GenAI-native and/or Big Tech firms, we find that the use of such technologies creates a complex web of relationships. We see that incumbents are cultivating new complementary assets to buffer against disruption, analogous to Tripsas' (1997) seminal work and more recent research on incumbent adaptation (Bayus and Agarwal, 2007; Danneels, 2011) and disruption through complements (Adner and Lieberman, 2021; MacDuffie, Jacobides, and Tae, 2024). In the GenAI context, we specifically observe that executives perceive that assets such as proprietary data access, data cleanliness, and pattern-recognition capabilities are playing a key role, which they also expect to maintain. We also find that heterogeneity in organizational structure, particularly modularity, plays a critical yet understudied role in incumbent adaptation (Eggers and Park, 2018). These factors, combined with intrinsic barriers to GenAI displacement on a sectoral level, suggest incumbents anticipate a "levelling out" of average performers, leading to more uneven competitive landscapes. As such, we would expect regulation and the responses of key actors to have important effects on the competitive landscape. Our study advances the conversation beyond the "jagged" impact of GenAI (Dell'Acqua *et al.*, 2023), providing rhyme and reason behind its uneven effects across industries and firms, and cautioning against excessive enthusiasm of GenAI's presumed implications in every setting (Mollick, 2024).

2. Theoretical Background and Emerging Evidence

The emergence of artificial intelligence (AI), particularly generative AI (GenAI), presents a unique challenge to our understanding of technological change and its impact on organizations. Since the public release of ChatGPT in November 2022, GenAI has become the fastest-growing innovation in history, with some projections suggesting it could drive a $7 trillion increase in global GDP and boost productivity growth by 1.5% over 10 years (Goldman Sachs, 2023), and others suggesting a $4.4tn profit uptake (McKinsey & Co, 2023). Others are more circumspect, arguing that the architecture of GenAI technology primarily enhances efficiency in existing tasks rather than catalyzing transformative innovations. Acemoglu (2024), for example, projects a modest 0.53% increase in total factor productivity to account for the complexity of real-world tasks and the limitations of AI in fully automating them. Historical patterns underscore that the productivity benefits of new technologies often only materialize with difficulty and after significant lags and complementary innovations (Acemoglu and Restrepo, 2020; Brynjolfsson and Hitt, 2000; David, 1990; Rosenberg, 1998).

The stark contrast between these estimates reflects fundamental differences in assumptions about AI's applicability and potential for value creation, let alone disruption. Optimistic forecasts often presume widespread AI adoption, anticipating significant labor-augmenting effects (Brynjolfsson and Mitchell, 2017). Conservative estimates consider the challenges of implementing AI in complex, context-dependent tasks, question the magnitude of labor displacement (Acemoglu *et al.*, 2022; Acemoglu and Restrepo, 2018, 2020). They are skeptical about AI's ability to replicate human judgement in high-stakes decision-making contexts (Autor and Dorn, 2013; Sahoh and Choksuriwong, 2023), or of the economic merits of doing so at scale (Svanberg *et al.*, 2024).

Management scholars posit that AI is changing the sources of competitive advantage (Raisch and Krakowski, 2021; Wilson and Daugherty, 2018) but offer contrasting views on how this change occurs. Some argue that AI substitutes humans' cognitive capabilities (Balasubramanian, Ye, and Xu, 2022), while others propose that it complements them (Allen and Choudhury, 2022; Choudhury, Starr, and Agarwal, 2020; Murray, Rhymer, and Sirmon, 2021). Despite the emergence of studies looking at AI and, increasingly, GenAI's impact on task-level dynamics (Boussioux *et al.*, 2024; Dell'Acqua *et al.*, 2023; Svanberg *et al.*, 2024), little research has examined how these task-level dynamics aggregate to organizations or sectors and how they influence competitive advantage.

To obtain guidance on how competitive landscapes may be affected, we can turn to established theories of technological change. These point to the interaction between technology and specialized complementary assets and their owners (Teece, 1986). The classical view suggests that incumbents possessing necessary specialized complementary assets can maintain their competitive advantage even in the face of competency-destroying innovations (Helfat, 2002; Mitchell, 1989; Tripsas, 1997; Tushman and Anderson, 1986). However, misaligned complementary assets may become organizational rigidities, potentially hindering communication, learning, or decision-making (Benner, 2007, 2010; Cohen and Levinthal, 1989, 1990; Henderson and Clark, 1990; Tripsas, 1997). More recent work has looked at how disruption might happen not only in the focal market, but also through the rapid ascent of complements (Adner and Lieberman, 2021), which may either sustain or debilitate incumbents, which is why incumbents try to co-opt disruptors through ecosystems (MacDuffie *et al.*, 2024)

The emerging evidence in terms of the nature of AI (Iansiti and Lakhani, 2020; Jacobides *et al.*, 2021) indicate that the relationships may be a bit more complicated as with AI, a single technological change often exhibits simultaneous displacement and complementation dynamics, sometimes within the same complementary asset (Brynjolfsson and McAfee, 2014; Raisch and Krakowski, 2021). Such patterns can be observed by looking at the impact of AI on healthcare (Sogani *et al.*, 2020), media industries (Chan-Olmsted, 2019), and business-model innovation (Burström *et al.*, 2021). Also, while there is ongoing debate about whether AI qualifies as a "general purpose technology" (Bresnahan, 2024), it is clear that it requires concomitant organizational changes. Finally, the dynamics of AI and GenAI technology are concentrated in a relatively compact ecosystem of Big Tech players and private interests (Jacobides *et al.*, 2021), as evidenced by the remarkable growth of their AI capabilities.

Moving from AI to GenAI, there has been enthusiasm, especially from consultants, on the magnitude of its impact. While official adoption rates remain low, GenAI use is concentrated among large firms, high-growth start-ups, and certain geographic hubs (Sack *et al.*, 2024). In terms of its impact, research has focused on intra-firm performance distribution rather than inter-firm competitiveness. Preliminary evidence indicates that GenAI tools tend to benefit lower-performing employees more significantly, potentially narrowing skill gaps within organizations (Dell'Acqua *et al.*, 2023; Mollick, 2024). However, concrete data on the intra-firm correlates of variance remains elusive. Current research has primarily focused on firm-level adoption rates and broad economic impacts (Boussioux *et al.*, 2024; McKinsey & Co, 2024; Noy and Zhang, 2023), leaving a gap in our understanding of how GenAI affects individual and team performance within organizations.

As such, we have little to guide us on the extent to which GenAI can be expected to be "disruptive" (Christensen, 1997; Christensen and Raynor, 2010), in the sense of challenging those who currently hold competitive advantage. While we can extrapolate from studies on technological innovation more broadly, which consider whether innovations are "radical" or "incremental" (Henderson and Clark, 1990; Iansiti, 2000), whether expectations of the technology shape corresponding diffusion dynamics (Chari and Hopenhayn, 1991; Rosenberg, 1976), and whether innovations ultimately channel more value to the holders of certain complementary assets (Helfat, 2002; Mitchell, 1989; Tripsas, 1997), we have no concrete evidence on how this happens in reality. For all the focus on professions being challenged, or specific tasks and areas of work being automated (Boussioux *et al.*, 2024; Mollick, 2024), so far we lack either a theoretical basis or empirical evidence to guide us in this regard. This is the gap we aim to cover.

3. Research Design

3.1 Abductive Research

Our research employs an abductive approach, which seeks to identify unexpected phenomena within the context of relevant theoretical concepts (Pillai *et al.*, 2020) and develop straightforward explanations through empirically grounded reconceptualization (Timmermans and Tavory, 2012). As Ployhart and Bartunek (2019) note, in abductive research, the unexpected findings guide and inform the investigative process.

The abductive methodology frequently incorporates purposeful sampling and mixed methods, facilitating a triangulation approach (Jick, 1979) to reveal subtle anomalies (Katz, 2002). The choice of empirical context should be informed by preliminary considerations about where such anomalies might be found (Behfar and Okhuysen, 2018). A multi-phase, mixed-methods design allows for iterative evidence-gathering, gradually converging on a plausible interpretation of the anomalies present in the data (Bamberger, 2018). **Figure 1** outlines the stages to our abductive investigation, which we explain in detail in the text.

3.2 Empirical Setting

We chose the UK's Institute of Directors (IoD) as our research setting. The IoD is the largest organization in the UK for executives at director level and above, representing a broad cross-section of industries and organizational types. Our research project was conducted as a joint engagement with the IoD, funded by the UK's Regional Innovation Fund Knowledge Exchange Programme for the study of GenAI.

The setting was chosen on conceptual grounds rather than for representativeness (Miles and Huberman, 1994). While IoD membership covers many sectors, professional services constitutes the largest. This composition allowed us to leverage granular differences within sectors—for example, comparing regulated and non-regulated professional services. IoD also encompasses executives from a wide range of firm sizes, from entrepreneurial startups and micro-enterprises to large institutional players. This variance helped us better able to tease out the central concepts and underlying mechanisms.

The IoD is a relevant context for five reasons. First, by focusing on senior executives and their experiences and expectations, we offer a distinct perspective. While much current research on AI takes a bottom-up approach, where the unit of analysis is the worker or task (Acemoglu and Restrepo, 2018; Brynjolfsson *et al.*, 2023; Dell'Acqua *et al.*, 2023; Noy and Zhang, 2023), our approach affords a strategic, organizational-level view of GenAI's impact drawn from executive perceptions.

Second, given the extensive debate over the potential impact of AI in knowledge-intensive sectors, the IoD's high representation of these sectors offers a unique sample to uncover these dynamics. This departs from prior literature examining technological shocks affecting task-level automation (Autor and Dorn, 2013; Brynjolfsson and McAfee, 2014) and aligns more closely with the specific challenges and opportunities presented by GenAI.

Third, the IoD sample provides relevant variance in sectoral and organizational characteristics while controlling for the level of seniority. The concentration of executives in the UK also controls for factors that may be correlated with geography or regional effects, allowing us to isolate the impact of organizational and sectoral factors.

Fourth, by focusing on a specific period and executives from a stable membership base, we minimize the risk that exogenous events, such as technological adaptations, could contaminate the later stages of our research (Creswell and Plano Clark, 2018).

Fifth, and perhaps most important, the views of Directors in such an uncertain strategic environment are interesting in and of themselves, as they are consequential, since Directors decide where to allocate funds and how to engage with such technologies. As such, while their perceptions may prove misguided, they will share their firms' future, and thus become important to document.

While our sample provides unique insights, it is important to acknowledge potential limitations. Our study may be subject to self-selection bias (Heckman, 1979), likely capturing executives who are more engaged with or knowledgeable about GenAI. However, this characteristic enhances the study's relevance in the context of emerging technologies. Given the current phase of GenAI development, where use cases are not yet clearly defined, insights from early adopters and enthusiasts are particularly valuable (Rogers, 2003). Notably, it is precisely because of this self-selection that our observation of heterogeneity in experiences and expectations regarding the technology becomes especially revealing.

3.3 Mixed Methods: Open-Ended Roundtables, Survey, and Structured Roundtables

Our mixed-methods abductive design comprised three stages, as shown in **Figure 1**. Our initial focus was on sectoral dynamics, with the hope that the focus on how firms in different settings are affected distinctly by GenAI would offer fresh insights. Our research questions were: (1) *What is the current state of GenAI adoption across different sectors? (2) What barriers and enablers do executives observe?* and *(3) What is executives' assessment of how transformational GenAI is, or could be, in their sector?* Qualitative fieldwork collected insights to unpack these research questions. We conducted five open-ended roundtable discussions in early February 2024, interviewing a total of 96 executives with an average of 19 participants per roundtable and identified three initial patterns: (1) a wide range of barriers and enablers at both organizational and sectoral levels; (2) significant intra-sectoral variance in expectations and experiences of GenAI adoption; and (3) varying perspectives on the potential impact of GenAI across sectors.

Having confirmed executives' varied perceptions, we refined our research question to explore this heterogeneity. Also, given that much of the discussion revolved around expectations—since only limited changes had actually taken place—we adapted our focus and questions. Thus, in Stage 2, we asked: *How are differences in organizational and sectoral characteristics associated with experience and expectations of GenAI's disruptive potential?* To unpack this question, we conducted a structured survey with 217 executives from mid-February to March 2024, searching for systematic patterns that underpin their experiences and expectations of

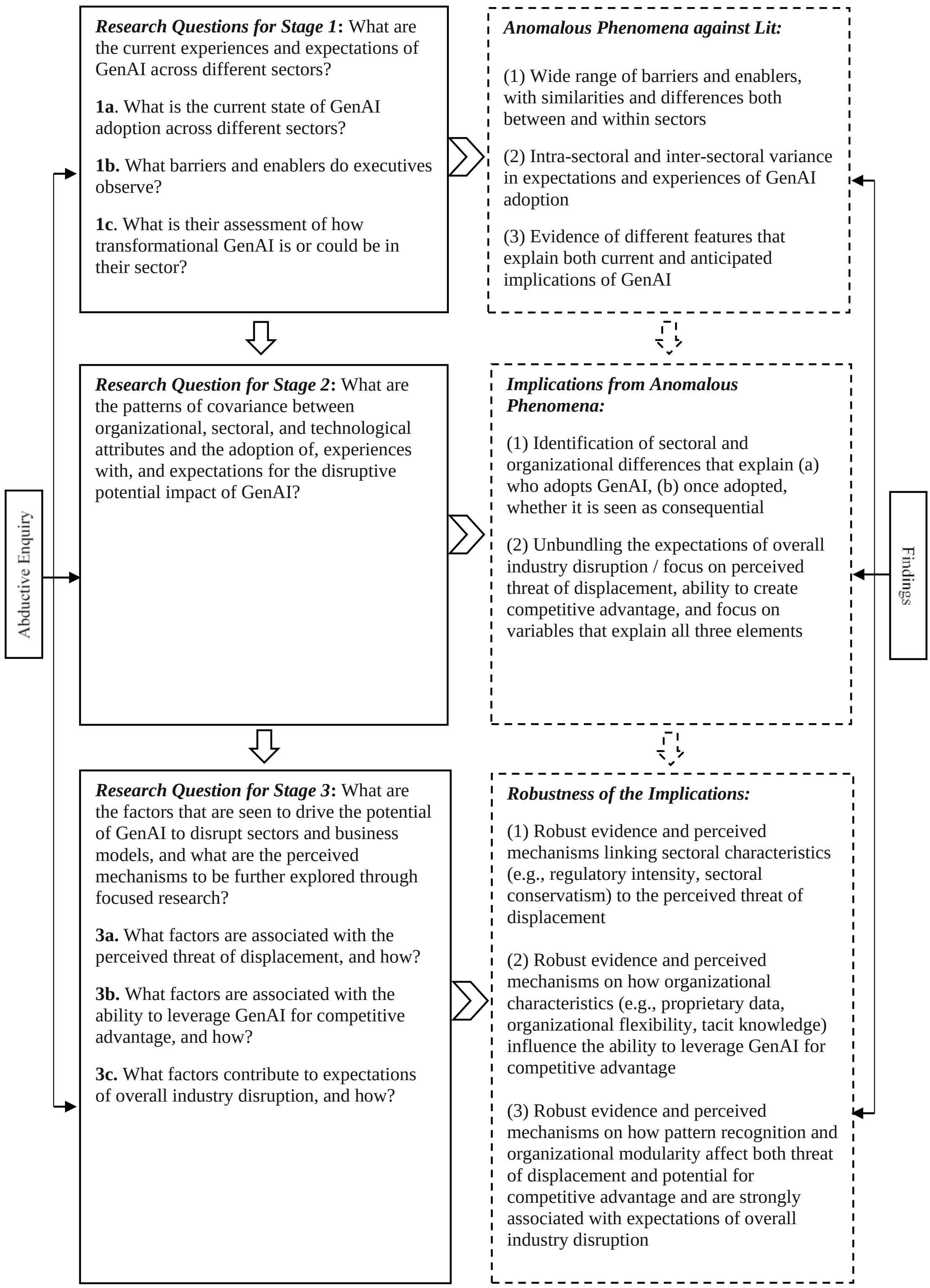
GenAI. The exploratory investigation identified sectors with greater variance in organizational adoption, experiences, and expectations of GenAI. It also revealed distinct sets of variables associated with the perceived threat of displacement, ability to create competitive advantage, and expectations of overall industry disruption. Notably, the importance of proprietary data and pattern recognition emerged as significant predictors across multiple dimensions.

Third, because the quantitative findings in Stage 2 reinforced and expanded upon the qualitative insights in Stage 1, we drew on the patterns we could observe and aimed to reach a better understanding of what lay beneath them. Thus, we probed more deeply through three interrelated questions: *(1) What factors are associated with the perceived threat of displacement, and how? (2) What factors are associated with the ability to leverage GenAI for competitive advantage, and how?* and *(3) What factors contribute to expectations of overall industry disruption, and how?* To address these questions, we conducted nine structured roundtables from late March to May 2024: seven comprising survey respondents selected based on their scores on key variables and two including external executives for an outsider perspective, interviewing a total of 163 executives with an average of 18 participants per roundtable. Our analysis revealed that the perceived threat of displacement was primarily associated with sectoral characteristics such as regulatory intensity and sectoral conservatism, although organizational factors such as reliance on technical knowledge also played a role. Conversely, the ability to leverage GenAI for competitive advantage was more closely tied to organizational characteristics, including the importance of proprietary data, organizational flexibility to experiment, and the role of tacit knowledge. Two factors—pattern recognition and organizational modularity—emerged as significant in both the threat of displacement and the potential for competitive advantage and were also strongly associated with expectations of industry disruption.

Finally, we assessed the robustness of our implications by examining the evidence and perceived mechanisms linking sectoral and organizational characteristics to the various aspects of GenAI's impact. Overall, the chronological progression of our mixed-methods abductive design helps develop implications from the observed phenomena in GenAI adoption and expectations and ensures the robustness of those implications from multiple angles.

Our mixed-methods approach, while comprehensive, has inherent limitations. Roundtable discussions may introduce social desirability biases (Nederhof, 1985), potentially influencing executive responses. Nevertheless, there is reason to suggest these methodological constraints do not question the validity of this study's findings. Despite potential pressures for conformity, we observe significant heterogeneity in perspectives among executives from similar sectors, which is noteworthy given the current lack of a dominant design in GenAI applications (Abernathy and Clark, 1985; Anderson and Tushman, 1990; Arthur, 1989; Eggers, 2014; Suárez and Utterback, 1995). The persistence of varied industry perceptions, even in settings that might incite convergence, and vivid discussion with differing views, is promising. We encouraged and leveraged debate and contrasting viewpoints, enabling an exploration of sector-specific dynamics.

Figure 1: Progression of the abductive analysis



4. Stage 1: Observations from Initial Roundtables

4.1 Methodology

As Timmermans and Tavory (2012: 179) note, an abductive inquiry “does not occur randomly but often begins with inhabiting a marginal structural position in a broader intellectual milieu that stifles ambition.” With this in mind, we start our abductive inquiry with a focal question: *What are the current experiences and expectations of GenAI across different sectors?* (We do not identify specific individuals or businesses for reasons of confidentiality.)

Table 1: Descriptives of Stage 1 roundtable participants

#	Theme	Participants	Industry Coverage
1	Non-regulated professional services	19	Management consulting, technology consulting, engineering and construction consulting, healthcare and life sciences consulting, education consulting
2	Omnibus (1)	20	Education, management consulting, finance and risk management, technology and energy, data analytics, professional training, software development
3	Media and communications	19	Communications, PR and marketing, media production, advertising, market research, business services
4	Regulated professional services	16	Legal services (corporate law, litigation, patent and trademark law, immigration), insurance, banking, management consulting
5	Omnibus (2)	22	Management consulting, technology consulting, financial services, banking, engineering and construction consulting, pharma, life sciences

The interviewers asked roundtable participants how they saw GenAI within their organizational context, probing barriers, enablers, and the potential for sector transformation. Participants were encouraged to share their own perspective and comment on that of others, and to be as concrete and context-specific as they could. We sought to scope out as many different perspectives and attributes (Furnari *et al.*, 2021) as possible, without attempting to determine which were the most significant or impactful. The appendix offers details on the participant composition of the roundtables and the state of GenAI adoption between and across sectors, top-down and bottom-up.

4.2 Why Does Heterogeneity Arise in GenAI Experiences within Sectors?

Our research approach aimed to gauge the variation in participants' experiences with GenAI within their respective sectors. To do so, we prompted participants to discuss how their organizations used GenAI. This revealed that positive experiences were attributed to different reasons and that GenAI had been enabled by varied patterns of resource ownership—even within the same sector.

Executives identified different organizational resources that they believed enabled greater differentiation through GenAI. We categorized these resources as enablers; they are summarized in the left column of **Table 2**.

For instance, two PR executives reported positive experiences with GenAI as a source of differentiation. However, one emphasized their employees' superior writing skill, which they speculated was enabling better "prompting" than competitors could achieve. The other highlighted their reservoir of proprietary PR documents they were using to super-scale GenAI capabilities.

Some executives mentioned the value of proprietary data from prior client work and pitch decks, which they were using to scale up work and synthesize more unique outputs. Others emphasized the importance of relational capital, noting that the advent of GenAI had exacerbated issues around clients' perceptions of quality. Organizational trust was cited as a key differentiator, with existing relationships proving crucial in maintaining clients' confidence.

Some participants openly disagreed on which aspects of their services were most critical in the face of GenAI adoption. One advertising executive attested to positive complementarities between human labor and GenAI technology: "Even though the technical knowledge itself of how to create advertising campaigns is not going to be as useful […] the people with the technical knowledge still are needed to use GenAI to generate differentiation." In contrast, another advertising executive emphasized how they were leveraging their firm's historical data: "GenAI is based on the uniqueness and depth of your data, which [our firm] has mountains of." They added that their small organization was already experimenting freely with GenAI applications, unencumbered by the legacy or reputational concerns of larger competitors. Other executives within the same sector identified different organizational impediments to leveraging GenAI. We categorized these factors as barriers, summarized in the right column of **Table 2**.

Several executives in non-regulated professional services reported challenges related to organizational complexity and modularity. One executive from a management consulting firm noted that while their firm was eager to deploy the technology, the complexity of their organizational structure made it difficult to decide at which level(s) to do so. "There is just a lot of layers to get through before we can use the technology. GenAI is good at replacing [individual] tasks, but an organization is a system of tasks." While executives in management consulting generally agreed that the nature of their work made seamless deployment of GenAI difficult, some said they were close to having a blueprint for deployment. The challenge of integrating new technologies with existing architecture was echoed across sectors. As a director in an investment bank recounted, "A few years ago, we acquired this small tech firm in order to digitalize our backend. It was a complete failure; you realize that the technology stacks just don't fit together. The engineers […] spoke different languages. It's a similar experience for us with GenAI."

Executives also reported barriers related to organizational leadership and understanding of the technology. One director of a consulting firm asserted, “CEOs are at the position they are at because what they have done has worked for the past decade. It’s not in their interest to invest in this transformative and uncertain technology.” While some media and communications participants attributed this to CEOs’ lack of interest and risk appetite, others argued that the technology was simply too advanced for CEOs to comprehend fully.

Talent emerged as another significant barrier. As one advertising executive noted, “It’s not that we don’t want to use the technology, and we can clearly see some of our competitors already using it. We just don’t really have the right people within our organization to lead its implementation.” Some executives linked this challenge not merely to the size or legacy of the firm, but more to its reputation.

4.3 Why Does Heterogeneity Arise in GenAI Experiences across Sectors?

In the latter part of the roundtables, we went on to explore participants’ experiences and expectations regarding the transformative potential of GenAI within their sectors. We encouraged executives to consider how GenAI was already affecting their industries and how it could potentially reshape industry dynamics. We actively facilitated debates among participants, prompting them to discuss and challenge each other’s views.

Executives in law and financial services displayed more aligned experiences with GenAI. They consistently evinced greater excitement over the technology’s potential to benefit incumbents and less concern about new entry or displacement. These participants often characterized significant industry disruption as “unlikely in the foreseeable future,” focusing instead on localized productivity gains. In contrast, executives from non-regulated professional services presented a wider spectrum of perspectives. Some framed GenAI as an “existential threat” to their sectors, reporting that they were actively “reevaluating their corporate purpose" and “searching" for new sources of value creation. Others viewed GenAI through the lens of technological hype cycles, drawing analogies with technologies such as blockchain or industrial inventions such as the tractor. As one skeptical participant elaborated, “And beyond just the return on investment, is it going to be sustainable as a financial gain? Because [the hype cycle] reaches a peak, the technology and the conception of it, and then there’s disappointment, and then there’s a production kind of plateau. And I think […] [GenAI] is going to follow this pattern as well […].”

This heterogeneity in perspectives led us to investigate the underlying factors that might explain these sectoral differences. Our inquiry revealed three key “buffers” that appeared to mediate executives’ concerns regarding the threat of displacement or incumbent displacement.

The role of legal liability in value offerings emerged as a significant buffer, particularly in regulated professional services. As one legal executive noted, “Sure, there may be some clients who need basic legal advice, and ChatGPT might help with that. But most of our big clients, most of the big fish, are hiring us more for the certification of our advice. We provide legal liability, so they have extra insurance. They can’t sue the AI if it gives them wrong advice.” A director in a strategy consultancy echoed this sentiment: “I’ve run a consultancy for 20 years, and consultants are brought in for many different reasons […] But […] sometimes it’s just because the top management won’t listen to their own management, and they need an independent voice.”

Output accuracy emerged as another buffer, particularly in the insurance industry. One executive stressed, “Our sector demands precision upon precision. A miscalculation could be catastrophic. It’s not something we can compromise on.”

Table 2: Enablers and barriers linked to GenAI experience (Stage 1)

Enablers	Barriers
Proprietary data being supercharged/unlocked through GenAI • “We’ve found that we’re essentially sitting on a goldmine. We have this library of press releases that we’ve not been able to properly use until now. Now we can replicate at scale our writing style” (Director in PR firm, Roundtable 3) • “What we are doing currently with GenAI is using our library of prior data and super-scaling it with the tech, [..] seeing if that can even create new business opportunities for the firm." (Director in law firm, Roundtable 4) *Tacit knowledge in human labor complementing GenAI’s lack of judgement* • “The technology is impressive, but it’s not going to take your job, because it can’t. It doesn’t have human intelligence. But in the right human hands, it’s very powerful.” (Managing Director in construction consultancy, Roundtable 1) • “ChatGPT can give me a bunch of facts, but […] it’s still the job of the consultant, and his experienced judgement, that is needed to determine which facts matter and which don’t.” (Director in strategy consultancy, Roundtable 1) *Technical expertise in humans correcting and verifying GenAI’s output inaccuracy* • “Normally, we end up with a team of 20 or 30 developers writing code [...] There will almost always be a bug [...]. Now, our company got an AI tool […] It still required [...] a high-level developer to check that code [...] But he said it saved him two weeks of work." (Director in software development firm, Roundtable 2) *Relational capital and client trust buffering the firm against selection issues* • “It’s a matter of trust about whether the quality of your advice is good enough. If you’re using these AI tools as co-thinkers, […] can you prove to me that what you’ve got through […] AI is trustworthy?” (Logistics director, Roundtable 1) *Organizational risk appetite enabling adoption and first-mover advantage* • “If you’re an organization that sits in the pie of a market, you just have to eat your little slice, you’re finished. Because someone else who isn’t will kill you at a quicker pace than anything normally happens in the commercial market. If you’re someone who’s willing like Elon Musk, you don’t want that pie, you want to create a pie.” (Director in educational consultancy, Roundtable 2)	*Lower modularity increasing the complexity of deploying the technology* • “There is just a lot of layers to get through before we can use the technology. GenAI is good at replacing [individual] tasks, but an organization is a system of tasks.” (Director of management consulting firm, Roundtable 1) • “But the problem is big corporations are tied to standards [for] standardization. The deployment of new technologies, things like that, are not very favorable […] In a small organization, it’s very welcome. But a bigger corporation would see it as risk.” (Director of education technology firm, Roundtable 2) • “A few years ago, we acquired this small tech firm in order to digitalize our backend. It was a complete failure; you realize that the technology stacks just don’t fit together. The engineers […] spoke different languages. It’s a similar experience for us with GenAI.” (Director of investment bank, Roundtable 5) *Organizational leadership being uninterested or not understanding the technology* • “CEOs are at the position they are at because what they have done has worked for the past decade. It’s not in their interest to invest in this transformative and uncertain technology.” (Director of consulting firm, Roundtable 4) • “Executives are, at the end of the day, risk-averse people. It does not help that the ROI of this technology is difficult to measure or understand.” (Director of financial services firm, Roundtable 2) *Inability to identify and/or attract the right talent to deploy the technology* • “It’s not that we don’t want to use the technology, and we can clearly see some of our competitors already using it. We just don’t really have the right people […] to lead its implementation.” (Director at advertising firm, Roundtable 3) • “Our organization is small and not as well-known as some of these bigger players in our sector. We struggle with the pull to bring [in] the right engineering talent, or even to know who they are.” (Director at EdTech firm, Roundtable 2) • “We're already experiencing what was a talent drain in a few years before GenAI and over COVID. Lots of people leaving the local sector to go to other sectors, and a lot of technical minded people […] This means that only the top companies with the big budget and big resources are now able to attract people back.” (Director at technology firm, Roundtable 2)

The third buffer was behavioral conservatism or norms of conduct, particularly in financial services, where executives mentioned a sectoral culture of technological conservatism: “We are notoriously slow, and it’s just how we are with technology.”

These sectoral buffers appeared to influence the extent to which executives believed GenAI was currently affecting their positions and would continue to do so in the future. Executives from sectors with stronger buffers, such as legal and financial services, tended to exhibit lower variance in their perspectives and less concern about immediate disruption. In contrast, executives from sectors with weaker buffers showed greater diversity of opinion and higher levels of concern about potential disruption. The presence and strength of these buffers varied across sectors, seemingly contributing to heterogeneity in GenAI experiences and expectations.

5. Stage 2: Structured Survey and Analyses

According to Timmermans and Tavory (2012), making sense of anomalies “rests on the cultivation of anomalous and surprising empirical findings […] through systematic methodological analysis.” To systematically examine the anomalous findings from the qualitative roundtables, we conducted a survey to unpack our refined research question: *How are differences in organizational and sectoral characteristics associated with experiences and expectations of GenAI’s disruptive potential?* We developed the survey instrument based on insights from the Stage 1 roundtables and constructs selected from the literature. The survey, run on Qualtrics, probed IoD members’ assessments of GenAI adoption barriers and enablers, current and anticipated implications, and perceived disruptive potential across organizational functions and industry sectors. It included closed-ended items using Likert-type scales to capture these variables.

5.1 Survey and Data Collection

We developed Likert-type scales to measure organizational characteristics, functional GenAI adoption, and expected GenAI impact. To maximize response rates, we kept the questionnaire brief, which limited use of existing scales. Control variables included firm size (annual turnover and employee count), executive technology attitudes, and industry sector. We randomized question items and centered Likert scales to mitigate autocorrelation. For example, proprietary data, a variable drawn from our Stage 1 roundtables, was measured using a 5-point Likert scale response to "How important is proprietary data to your firm's business success?"

We pretested the survey instrument with 10 IoD members over individual one-hour interviews before administering it, in English, to the entire IoD membership database via email. Our IoD liaison sent the initial invitation, followed by two reminder emails during the data collection period. The survey was administered in February 2024, with results collected over a two-month period. We received 217 complete responses from our sample of approximately 2,000 IoD members, representing a response rate of about 10.85%.

The survey targeted executives at director level and above, with 29.60% of respondents being CXO/president and 45.74% at director level. All respondents confirmed their executive-level status in response to a survey question. To develop a representative sample of UK firms, we allowed participants to self-select into responding, with no specific exclusion criteria. To ensure data quality, participants were informed that they would receive a personalized benchmark of how their organization performed against peers, a common method to enhance the validity of self-reported survey data.

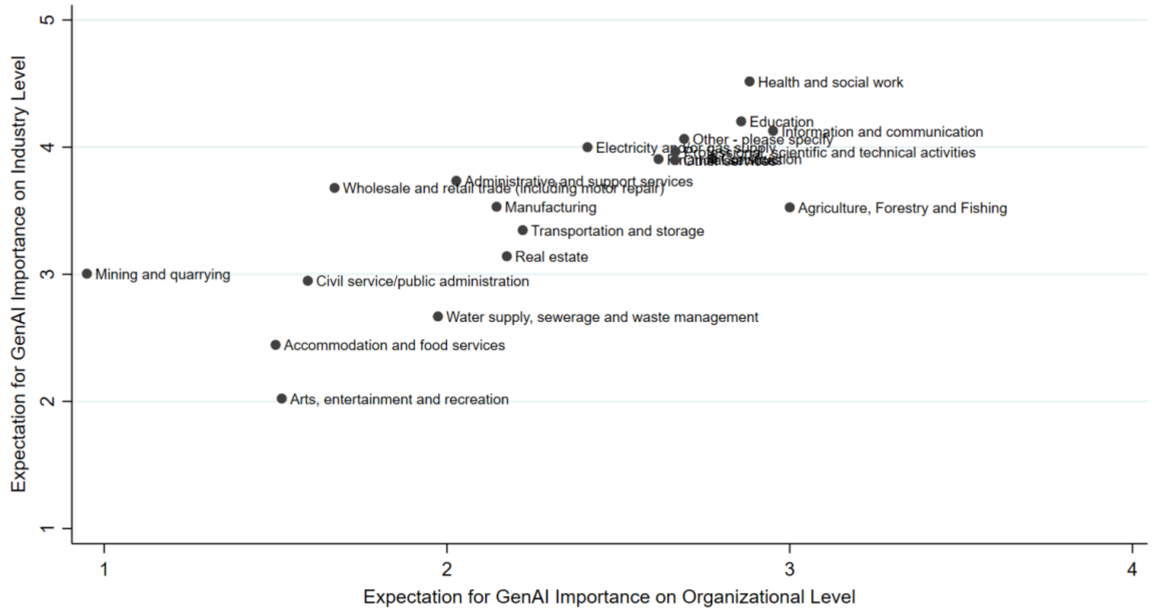
5.2 Findings and Implications

In this section we summarize key findings of our descriptive analyses and cross-sectional regressions; more detail is available in the appendix. In all, Stage 2 analysis corroborates many of the propositions developed in Stage 1, while also revealing several anomalies that merit further examination in the subsequent and final stage of our abductive analysis.

Firstly, we find supporting evidence for the proposition from Stage 1 that most organizations have begun integrating GenAI into their operations, albeit with varying experiences. Our survey data reveals that 72% of respondents report some impact from GenAI—yet only 23% indicate significant or transformative effects, with a mere 9% reporting transformative impacts. We also observe higher overall GenAI engagement from larger firms, but a greater proportion of smaller firms reporting transformative impacts (12% of small firms versus 5% of large firms).

Secondly, we find evidence supporting the Stage 1 observation that executives identify different enablers and barriers to GenAI adoption, even within the same industry. Our survey data corroborated this and further revealed a more nuanced finding: executives seem to have higher expectations of GenAI's transformative potential at the industry level than within their own organizations. This discrepancy was more pronounced among respondents from larger firms. **Figure 2** also showcase sectoral differences.

Figure 2: Expected importance of GenAI by sector: industry vs. organizational level



Source: IoD survey data

Thirdly, we observe divergent perceptions among executives regarding expectations for GenAI's potential to unlock new forms of distinctiveness and for it to displace existing offerings. For example, the distribution of responses concerning new forms of distinctiveness exhibited unimodal properties with a positive skew, with 81% of executives perceiving at least some positive potential and only 7% anticipating erosion of distinctiveness. In contrast, perceptions of GenAI's impact on displacement exhibited a more uniform distribution. While 28% of executives believe displacement will become "extremely difficult," 12% anticipate it becoming "extremely easy," reflecting a broader range of expectations regarding displacement.

All in all, our descriptive patterns suggest that separate sets of factors influence executive perceptions of GenAI's potential to increase distinctiveness and its threat of displacement. To investigate this proposition further, we employed ordinal logistic regression (OLR) models to examine factors associated with executives' perceptions of GenAI's disruptive potential. We chose OLR in order to preserve the natural ordering of many of our variables and to allow for non-linear relationships between independent variables and ordinal outcomes (Long and Freese, 2006), although we observe similar results using generalized ordered logistic models.

Our OLR results corroborate the proposition. Different factors appear salient for competitive imitation threat compared to distinctiveness potential, confirming our earlier proposition. A set of our results are shown in **Table 3**. For displacement threat, the perceived importance of market insight emerges as a significant predictor (OR = 0.692, p = 0.038). This suggests that sector-specific dynamics shape perceptions of likelihood of displacement. Firms valuing proprietary data perceive a decreased likelihood of displacement threat (OR = 0.700, p = 0.004). Conversely, organizational assets appear more relevant for distinctiveness potential. Firms emphasizing proprietary data (OR = 1.290, p = 0.038), pattern recognition capabilities (OR = 1.565, p = 0.000), and relational knowledge (OR = 0.548, p = 0.002) show greater expectations for distinctiveness, indicating that executives view these as key differentiators in leveraging GenAI for competitive advantage. Additional analyses can be found in the appendix.

Table 3. OLR models predicting relevance of Stage 1 enablers

	Potential for GenAI Distinctiveness	**Threat of Displacement**	**Impact of GenAI in Industry**
Firm size (turnover)	0.777 (0.070)	1.208 (0.110)	0.800 (0.075)
	[.005]	[0.038]	[.017]
Regulation	1.219 (0.164)	0.972 (0.126)	1.258 (0.178)
	[.143]	[0.830]	[.104]
Modularity	1.040 (0.213)	0.873 (0.176)	1.534 (0.329)
	[.848]	[0.500]	[.046]
Proprietary data	1.290 (0.158)	0.700 (0.863)	1.134 (0.144)
	[.038]	[0.004]	[.319]
Technical knowledge	1.077 (0.180)	1.112 (0.191)	1.145 (0.197)
	[.657]	[0.535]	[.431]
Tacit knowledge	1.446 (0.299)	1.368 (0.295)	1.082 (0.224)
	[.075]	[0.146]	[.702]
Pattern recognition	1.565 (0.198)	0.998 (0.121)	1.300 (0.166)
	[.000]	[0.985]	[.040]
Market insight	1.310 (0.227)	0.692 (0.123)	1.298 (0.225)
	[.118]	[0.038]	[.131]
Relational knowledge	0.548 (0.107)	0.826 (0.153)	1.099 (0.206)
	[.002]	[0.304]	[.615]
LRχ^2	54.72	26.13	42.22
	[.000]	[.002]	[.000]
Pseudo R^2	0.079	0.040	0.073
Observations	217	217	217

Note: Coefficients reported in odds ratios. Robust standard errors in parentheses. p-Values are included in square brackets.

Together, these findings suggest promising theoretical leverage for asking in our subsequent stage: *What are the factors that are seen to drive the potential of GenAI to disrupt sectors and business models, and what are the perceived mechanisms to be further explored through focused research?*

While these patterns reinforce the general findings of Stage 1, several methodological considerations merit attention. Our cross-sectional data precludes causal inferences, and our results may be subject to common method bias. The use of self-reported measures from a single respondent per organization introduces potential biases. Moreover, our OLR models assume proportional odds across response categories—an assumption that may not always hold. To address this concern, we conducted additional analyses using generalized ordered logistic models, which yielded similar findings, thus enhancing the robustness of our results.

Notwithstanding these limitations, our findings thus far provide a clear picture of executives' perceptions of GenAI's disruptive potential. The consistent patterns justify our Stage 3 investigation, to which we now turn.

6. Stage 3: Insights from Follow-Up Roundtables

6.1 Data Collection

To address the questions emerging from Stages 1 and 2, we conducted a series of executive roundtables in two parts. Part A consisted of seven paired roundtables (A1–A4), strategically composed based on executives' survey responses from Stage 2. We designated these as follows: pattern recognition importance (A1a: high, A1b: low), proprietary data importance (A2a: high, A2b: low), strategic uncertainty (A3a: high, A3b: low), and modularity (A4: mixed). We interviewed 112 executives and averaged 16 participants per roundtable. Part B comprised two additional roundtables: B1 with 21 participants engaged in strategy and policy from the IoD and B2 with 30 executives primarily from private equity firms. In total, Stage 3 involved 163 executives at director level or above. Participant demographics are detailed in **Table 4**.

Table 4. Descriptives of Stage 3 roundtable participants

#	Theme	Participants	Industry Coverage
A1a	High pattern recognition importance	23	Pharmaceuticals, biotechnology, cybersecurity, insurance, management consulting, ESG assessments, behavioral science, environmental planning and landscape design
A1b	Low pattern recognition importance	13	Management consulting, venture capital, software development, environmental services, alternative dispute resolution, AI ethics certification, digital agency services
A2a	High proprietary data importance	17	Pharmaceuticals, management consulting, legal services (corporate, litigation), insurance, banking, technology advisory, corporate restructuring
A2b	Low proprietary data importance	15	Telecommunications, management consulting, venture capital, chemical manufacturing, marketing, medical services, construction, education
A3a	High strategic uncertainty	11	Management consulting, digital banking, technology solutions, risk and compliance advisory, real estate advisory, manufacturing
A3b	Low strategic uncertainty	18	Management consulting, technology, venture capital, legal services, chemical manufacturing, manufacturing, meteorology, food and beverage export
A4	Modularity (mixed)	15	Healthcare, pharmaceuticals, financial services, technology, management consulting, legal services, construction equipment supply, language translation
B1	Strategy & policy	21	Management consulting, banking, insurance, legal services, pharmaceuticals, telecommunications, ESG assessment, education
B2	Private equity	30	Private equity, venture capital, management consulting, legal services, technology, banking, retail

Part A roundtables addressed three key research questions: (1) *What factors are associated with the perceived threat of displacement, and how?* (2) *What factors are associated with the ability to leverage GenAI for competitive advantage, and how?* and (3) *What factors contribute to expectations of overall industry disruption, and how?* The roundtables followed an inside-out approach, beginning with organizational-level perceptions before extrapolating to sectoral-level analysis. The aim was to tease out the factors related to our three key dependent variables: perceived threat of displacement, ability to leverage GenAI for competitive advantage, and expectations of overall industry disruption. B1 and B2, meanwhile, provided a sense-check of our findings from A1–A4 and allowed us to explore perceptions of these factors and observations of the capabilities required to leverage GenAI from an "outside-in" perspective.

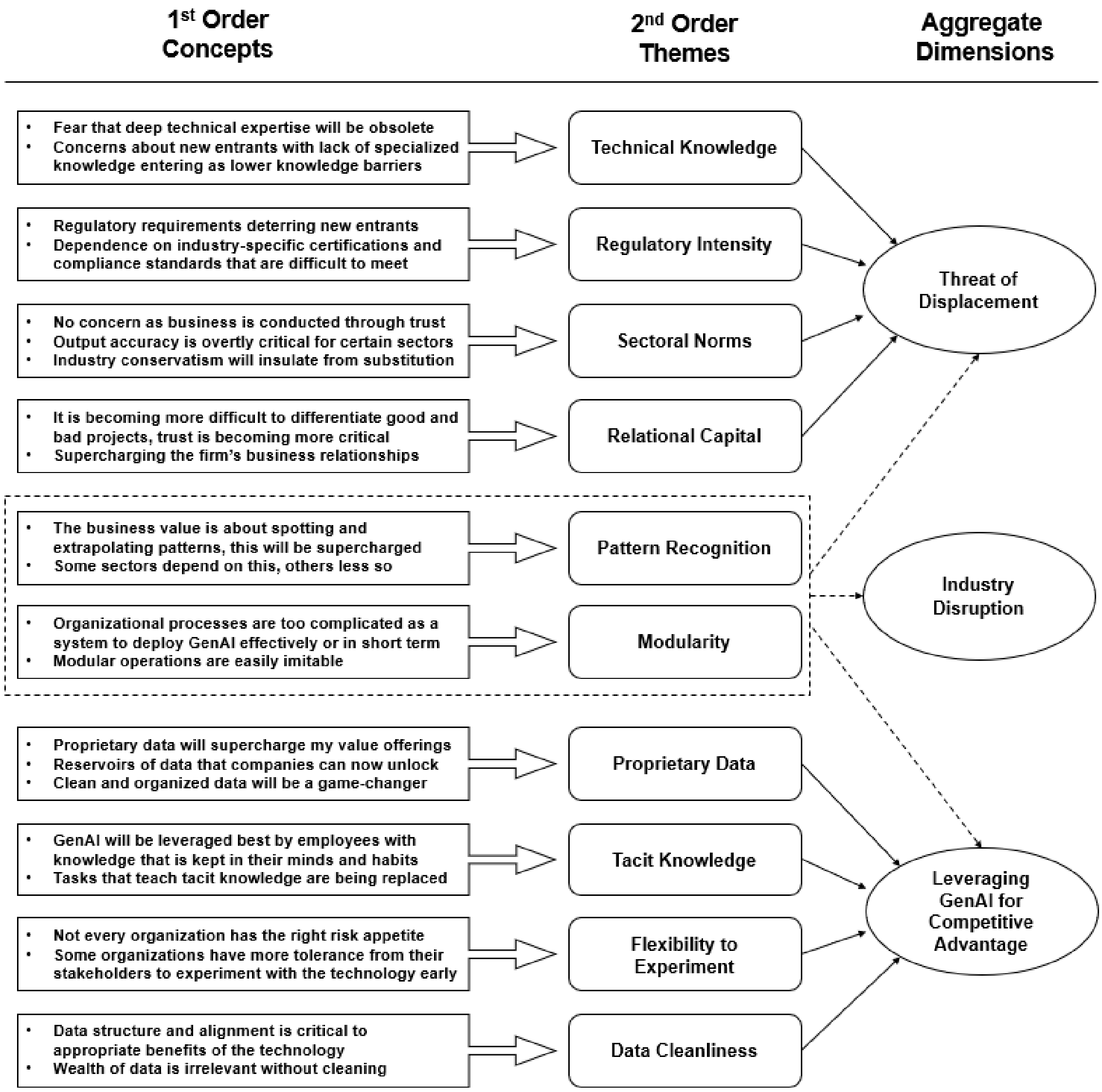
Each roundtable lasted 2.5 hours and was conducted in a hybrid format, with most participants attending in person. B2 lasted 4.5 hours and was an exclusively in-person event. Discussions were semi-structured, with interviewers encouraging participants to relate responses to their specific organizational and sectoral contexts and engage with each other. Sessions were video recorded and annotated by interviewers.

Our analysis of the roundtable data followed three main approaches: (1) comparative analysis of paired roundtables (e.g., high vs. low proprietary data importance) to identify divergent perspectives on the same stimuli; (2) cross-variable analysis, comparing responses from participants who scored high on one variable but low on another, to uncover potential interactions between variables; and (3) longitudinal insights from participants who had transitioned between sectors or companies with differing characteristics (e.g., from low- to high-regulation environments). This multifaceted approach allowed us to triangulate findings and develop a more nuanced understanding of how different variables interact to shape executives' perceptions of GenAI's impact on their industries and organizations.

6.3 Coding and Sensemaking

Following transcription, each author independently coded one representative roundtable. We then convened as a team to discuss any discrepancies and establish a standardized coding scheme to apply to the remaining roundtables. Throughout the coding process, the authors continued to meet regularly to adapt the coding scheme as needed. These initial discussions also enabled us to refine our interview protocol, focusing on emerging themes deemed most important by our informants and holding significant theoretical potential (Charmaz, 2006). We adhered to the inductive concept development methodology outlined by Gioia, Corley, and Hamilton (2013). We initiated open coding (Charmaz, 2006) by identifying first-order concepts directly from the informants' own words, capturing the essence of their implicit beliefs (Guba and Lincoln, 1982). Subsequently, we employed axial coding to identify higher-level, theoretically interesting patterns.

Figure 3: Thematic coding from first-order concepts to aggregate dimensions



We examined these second-order themes for concepts that might help us describe and explain the phenomena we were observing (Gioia *et al.*, 2013). By analytically distinguishing these emergent concepts, we aggregated the second-order themes into broader aggregate dimensions (Gioia and Chittipeddi, 1991), offering a theoretically intriguing perspective on executives' implicit theories regarding GenAI in strategic management.

Throughout this process, we iterated between the emergent concepts, themes, and dimensions from our interviews and the existing literature on strategic management and GenAI. This iterative analytical approach formed the basis for the data structure depicted in **Figure 3**. A detailed list of coded themes and quotes can be found in the appendix.

6.3 Findings: Displacement, Differentiation, and Disruption

Our data structure in **Figure 3** outlines the mapping of factors associated with perceptions of GenAI displacement threat, the ability to leverage GenAI for competitive advantage, and overall industry disruption. In following with our observations from Stages 1 and 2, we find generally distinct sets of factors influencing executive perceptions in each of these dimensions.

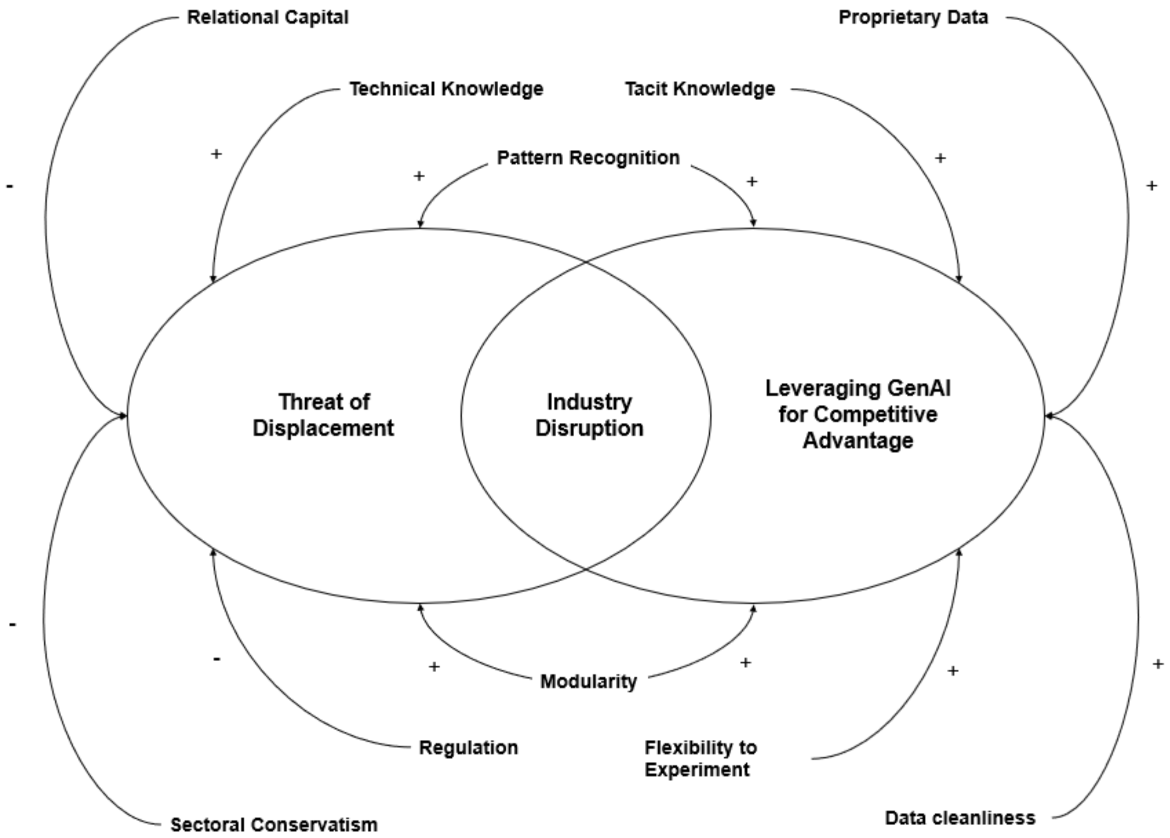
Our analysis revealed that four factors predominantly residing at the sectoral level moderated the perceived threat of displacement from GenAI: regulatory barriers, sectoral conservatism, relational capital, and reliance on technical knowledge. Concurrently, four firm-specific factors at the organizational level were linked to perceptions of the ability to leverage GenAI for competitive advantage: proprietary data, data cleanliness, tacit knowledge, and organizational flexibility to experiment. These two sets of factors operated independently of each other, with sectoral characteristics primarily moderating perceptions of displacement threat and firm-specific resources and capabilities moderating perceptions of the ability to generate competitive advantage. Details of our coding schema and illustrative quotes can be found in the appendix.

We further observed that the two dimensions of GenAI displacement and differentiation, in certain instances, covaried with two particular factors: pattern recognition and modularity – and that in these instances of covariance, also intersected with expectations of industry disruption. For executives who reported pattern recognition as important to their firms' success, these instances also covaried with both heightened concerns about GenAI's potential to displace existing business offerings and recognition of greater opportunities for strategic differentiation. Similar covarying dynamics were observed in relation to organizational modularity—the degree to which an organization's structure can be separated and recombined. Executives in highly modular settings reported greater perceived threat of displacement, with recognition that individual modules could potentially be replaced by GenAI. However, these same organizations also identified comparatively more opportunities for strategic differentiation and experimentation with GenAI through the ease of deployment and targeted implementation. In this regard, our results highlight that GenAI is likely to affect disruption via displacement and differentiation alike.

6.4 A Conceptual Framework for Understanding GenAI

Figure 4 synthesizes our findings, presenting a visual representation of the interrelationships among factors. Our analysis reveals distinct sets of variables associated with two primary phenomena: the perceived threat of displacement and the perceived capacity to leverage GenAI for enhanced differentiation. Additionally, we identify two factors that simultaneously correlate with both these phenomena and the anticipated likelihood of industry disruption: displacement and differentiation. So how should we think about our findings seen as a whole?

Figure 4. Constructs and directionalities based on Stage 3 analysis



Firstly, our empirical findings qualify some of the emerging discussion on GenAI's potential for "wholesale" displacement (Brynjolfsson *et al.*, 2023; Stokel-Walker and Van Noorden, 2023). We find that executives primarily evaluate GenAI displacement at the *sectoral* level, mediated by their sectors' "buffers" against displacement, which relate to sector-level regulation—a feature that is likely to remain important regardless of the pace of technological change—and modularity, an ever-elusive concept (Baldwin, 2024; MacDuffie, 2013). As for differentiation through GenAI, it correlates with variables at the *organizational* level, where firm-specific assets reside. Our investigation into these assets revealed significant variation in their nature and anticipated differentiation mechanisms across firms.

On the whole, we find that it would be hard to entertain the optimistic outlook of all respondents combined, suggesting either that our respondents are unusually gifted (which we cannot discount as they are a non-random sample of those interested in GenAI) or that they might be underestimating the potential intensity of competition among many differentiated firms. Be that as it may, our finding of co-varying dynamics of displacement and differentiation suggests that executives anticipate a "levelling-out" effect within their sectors, where the advent of GenAI squeezes out average and poor performers while privileging their better-prepared counterparts.

Secondly, our finding that sectoral characteristics mediate executives' perceptions of displacement threat implies systematic differences in *who* executives anticipate competing against. Notably, the anticipated stability of the competitor set varies across sectors, contingent upon specific industry attributes. Executives in sectors characterized by high regulatory barriers, stringent output accuracy requirements, and reliance on relational capital perceive these attributes as effective buffers against new market entrants, thus anticipating a relatively stable competitive environment. In contrast, executives in sectors lacking such structural impediments to entry demonstrate greater openness to the possibility of new competitive forces emerging. This dichotomy in perception suggests that industry-specific factors play a crucial role in shaping expectations about the impact of GenAI on market structure and competitive dynamics. Even if executives' expectations are unfounded, they still provide valuable indications on how we might expect GenAI to combine with other sectoral and organizational features with disruptive effects, which may merit further study.

Finally, our findings indicate that a task-based perspective, which primarily focuses on whether GenAI displaces or augments specific tasks, may be insufficient for comprehending the full industry-level implications of this technology. This is important, as much of the excitement over GenAI (Boussioux *et al.*, 2024; Dell'Acqua *et al.*, 2023; Mollick, 2024) bases its predictions of wholesale change on whether GenAI can outperform humans at fairly specific and modular tasks (e.g., providing online customer support, as in Brynjolfsson *et al.*, 2023; or creating a new footwear strategy, as in Dell'Acqua *et al.*, 2023). In our study, participants focus on the way GenAI combines with other features to effect change, echoing longstanding evidence in the study of general-purpose technologies and their complements (Bresnahan, 2021, 2024) and suggesting that we should moderate our expectations for wholesale disruptive change.

In this regard, our analysis reveals that two factors—the extent of reliance on pattern recognition and the degree of modularity within a firm or sector—are significantly associated with executive perceptions for threat of displacement, differentiation potential, and anticipated industry disruption, advancing our understanding of disruption in complements (Adner and Lieberman, 2021; MacDuffie *et al.*, 2024). This also suggests that to understand GenAI's impact we need to move beyond task-level research and consider the nature of a firm's activities and the architecture of its value-creation processes as predictors of disruption. Our paper provides such a framework, summarized in **Figure 4**, as an initial starting point.

That said, we should note potential limitations in our methodology, particularly the risk of selection bias in our survey responses. The sample may over-represent executives who are more enthusiastic about GenAI, potentially skewing our results towards a more optimistic outlook. However, this potential bias is partially mitigated by the composition of our sample, which is predominantly drawn from knowledge-intensive sectors such as professional services. These sectors are frequently cited in the literature as being particularly susceptible to AI and GenAI-driven displacement (Dell'Acqua *et al.*, 2023; Mollick, 2024). The juxtaposition of these opposing forces—potential positive bias in respondent selection versus the inclusion of theoretically vulnerable sectors—provides a degree of balance to our findings. Nevertheless, this methodological consideration warrants caution in the interpretation and generalization of our results, and highlights avenues for future research to address these limitations.

7. Discussion

Calls have been growing for academics and business leaders to investigate the implications of AI, and GenAI in particular. We respond to these calls by providing rich qualitative and quantitative data presenting preliminary assessments from business leaders on their experiences and expectations of GenAI thus far. This yields several key insights.

First, we offer a comprehensive view of executive perceptions regarding GenAI's impact on organizations and industries. Our findings reveal a nuanced picture of executive expectations. We identify distinct sets of factors associated with different aspects of GenAI's impact. Factors related to the threat of displacement predominantly reside at the sector level, with executives invoking sectoral buffers to mediate perceived threats. In contrast, factors associated with the ability to leverage GenAI for differentiation and competitive advantage reside on the organizational level and show significant intra-sectoral variation, indicating the importance of firm-level capabilities and resources.

Second, we identify two key constructs—pattern recognition and organizational modularity—that appear to influence both the threat of displacement and the potential for competitive advantage. These factors consequently invoke discussions of overall industry disruption, suggesting their central role in shaping executives' perceptions of GenAI's transformative potential.

Third, we articulate two constructs of industry disruption: the threat of displacement and the potential for novel advantage, contributing to our understanding of disruption (Christensen, 1997). We show how these two dimensions, perhaps counterintuitively, co-vary, and why some firms may be excited about these changes even as the *average* firm in the sector might expect to find itself squeezed, suggesting that an increasingly uneven future lies ahead.

Fourth, we find that while GenAI may displace technical and potentially tacit knowledge, it complements proprietary knowledge. As the underlying technology of GenAI, LLMs, appear to be more broadly available, this suggests that our executives believe that the potential for disruption depends on the existence or importance of proprietary data.

Our study provides important early evidence on both the magnitude and direction of change driven by GenAI, offering one of the first examinations of the correlates of its impact across sectors and organizations. While recent literature has primarily focused on analyzing task-level changes (Agrawal, Gans, and Goldfarb, 2019; Brynjolfsson, Jin, and McElheran, 2021; Krakowski *et al.*, 2023) or aggregating task-level changes to a macro basis (Acemoglu, 2024; Acemoglu *et al.*, 2022; Acemoglu and Restrepo, 2020), our research brings the discussion back to the features that intrinsically make up a sector. This sector-level perspective offers a nuanced view of how GenAI is reshaping competitive dynamics, challenging simplistic narratives of uniform disruption. We find that the perceived impact of GenAI varies significantly both between and within industries, mediated by sector-specific factors such as regulatory intensity and organizational characteristics such as possession of proprietary data. This heterogeneity in impact aligns with recent work by McElheran *et al*. (2024), who find varying AI adoption patterns across industries. Moreover, our identification of pattern recognition and organizational modularity as key correlates influencing both the threat of displacement and potential for competitive advantage provides new insights for understanding the direction of

GenAI-driven change. These findings help inform the debate by moving beyond generalizations about the impact of AI to a more contextualized understanding of how different organizational and sectoral characteristics shape GenAI's transformative potential. Our research moves beyond simply acknowledging its "jagged" or uneven impact (Dell'Acqua *et al.*, 2023), and elucidates the mechanisms behind this jaggedness, offering a nuanced understanding of how and why GenAI affects industries and firms differently.

7.1 Theoretical Implications

Our study relates to several literature streams in strategic management. First, we address a limitation in existing adaptation theories regarding GenAI's impact, as the technology simultaneously exhibits competency-destroying and competency-enhancing features (Agrawal *et al.*, 2021; Krakowski *et al.*, 2023; Raisch and Krakowski, 2021). We identify specific areas where organizations perceive GenAI as either competency-enhancing or competency-destroying, advancing understanding of how firms navigate GenAI adoption and its competitive implications. We provide indications of how incumbents might leverage existing assets to navigate the GenAI transition, echoing Tripsas' (1997) findings on complementary assets' buffering effect. We also document expectations of GenAI disruption, by showcasing how it substitutes and complements (Adner and Lieberman, 2021; MacDuffie *et al.*, 2024), outlining the distinct if covarying forces of displacement and differentiation, which we hope will help structure future research.

Our study hints at the varying competency-enhancing and competency-destroying aspects of GenAI across different contexts. We consider how bottlenecks may shift to proprietary knowledge, echoing recent work by Bessen, Impink, Reichensperger, and Seamans (2022, 2023), and examine how firms of different sizes are positioned to benefit. In line with the proposition that possession of complementary assets may determine the dynamics of competitive landscape shifts between incumbents and new entrants, our study also pinpoints where organizations perceive these buffers and where they anticipate potential disruptions. This analysis provides early indications at the sector level of how incumbents might leverage their existing assets to leverage GenAI. While our research provides early indications at the sector level, it also paves the way for future investigations into how industry architecture, technological regimes, and ecosystem structures could be reshaped by the advent of GenAI technologies (Jacobides *et al.*, 2021; MacDuffie et al 2024).

Second, we illustrate complex interactions between tacit, technical, and proprietary knowledge within organizations adopting GenAI. We find that even though these categories of knowledge may reside within the same firm, they can still exhibit both positive and negative complementarities. By disentangling these knowledge types and their interactions, our study offers a more sophisticated understanding of the relationship between human capital and technology in the age of GenAI. We move beyond simplistic dichotomies of "AI versus humans" and consider how GenAI can augment or replace human knowledge work (Brynjolfsson and McAfee, 2014; Davenport and Kirby, 2016; Krakowski *et al.*, 2023). This shows how different forms of human knowledge combine with GenAI capabilities and how they co-evolve (Helfat and Raubitschek, 2018; Tripsas and Gavetti, 2000).

Furthermore, we show that even if GenAI is considered a general-purpose technology (Bresnahan, 2024; Bresnahan and Trajtenberg, 1995), its transformative impact is contingent upon its combination with other organizational elements and knowledge types. This contributes to the ongoing debate about the nature and implications of AI as a potentially disruptive technology (Christensen, 1997; Christensen and Raynor, 2010) by highlighting the critical role of complementary organizational knowledge in shaping the impact of AI. It also contributes to discussions on how firms create, transfer, and leverage different knowledge types for innovation and competitive advantage (Argote and Ingram, 2000; Teece, 1986, 2006).

7.2 Implications for Organizations and Policy

Our findings also suggest several potential implications for organizational strategy, though further research is needed to confirm these preliminary insights. First, firms may benefit from assessing both their industry position and their organizational capabilities related to GenAI. Factors such as proprietary data, data cleanliness, organizational flexibility, and tacit knowledge emerged as potential enablers for leveraging GenAI, indicating areas where capability development might be valuable. While executives expressed enthusiasm about various complementary assets, our findings do not provide clear direction on whether this excitement for differentiation will lead to new competitive moats or if these efforts will ultimately clash and erode potential advantages. While the specific meaning and importance of these constructs may vary across sectors, their emergence as significant factors warrants attention. Organizations may benefit from considering the interactions between these elements and how they relate to their specific context.

Our findings also hint at the possibility that differentiated strategies across industries may be beneficial, based on sector-specific characteristics and barriers to GenAI adoption. As the GenAI landscape evolves, organizations may need to balance sector-specific dynamics with organization-level capabilities to effectively navigate this new technological environment.

Our study also suggests several areas where policymakers may need to consider interventions to promote equitable and beneficial integration of GenAI across economic sectors (CMA, 2023; Jacobides, Brusoni, and Candelon, 2021; McElheran *et al.*, 2024). Policymakers might consider exploring frameworks for data democratization that balance broader access with privacy and intellectual property protection. This could involve examining data-sharing protocols or data trusts to facilitate collective advances while addressing data ownership and utilization structures. Our findings indicate that sector-specific policy approaches to GenAI adoption may be worth considering, including targeted interventions for high-potential sectors facing implementation barriers, while taking care not to inadvertently confer regulatory advantages on incumbents. The potential for GenAI to reshape business models and value creation processes across multiple sectors suggests that competition authorities may need to broaden their analytical scope. This could involve considering not only the concentration of GenAI production capabilities among a small number of firms but also the wider implications of GenAI adoption on market dynamics, vertical integration, and the potential for cross-sector disruptions.

7.3 Generalizability, Limitations, and Future Research

The question of generalizability arises in our study. Our research focuses on director-level executives from the UK IoD, providing insights into a developed economy with a sophisticated business landscape. While we believe our findings are likely to generalize to similar contexts, future research should determine the extent of this commonality across different economic and cultural settings. We caution against extrapolating our results directly to rapidly developing economies or regions with significantly different regulatory environments or AI and GenAI adoption rates. We also note that executives are often wrong about their understanding of technology (Kellogg *et al.*, 2024). It may be, for instance, that proprietary data, important for AI, will be less relevant for GenAI. Technology also moves extremely fast, with the potential of resolving many of the bottlenecks it creates and that executives document. Both executives' and our own expectations of this technology's impacts are likely to be mistaken. That said, our objective was not to provide an assessment of the impact that GenAI has today, let alone what it may be in the future, but rather to identify the attributes that complement it so as to provide a set of hypotheses that can be further explored on the basis of data available to us today.

Seen this way, several of the limitations of our study suggest avenues for future research. These include the need for quantitative testing of our propositions across larger, more diverse samples; examining how executive perceptions translate into organizational actions and outcomes; investigating variations in perception and strategy at different stages of GenAI adoption and organizational maturity; and refining the identified key constructs. Future research could also explore potential negative consequences and ethical considerations of GenAI adoption influencing strategic decision-making. Additionally, deeper investigation into the relationships among industry-level factors and their collective impact on GenAI adoption patterns would be valuable. For instance, studies could examine how regulatory intensity interacts with sectoral conservatism to influence the pace and nature of GenAI integration across different industries.

Our study offers a nuanced perspective on the strategic implications of GenAI, challenging simplistic narratives of uniform disruption across sectors. By identifying distinct sets of factors associated with the threat of displacement and the potential for competitive advantage, we reveal a complex landscape where both sectoral buffers and organizational capabilities play crucial roles. The emergence of pattern recognition and organizational modularity as key constructs influencing both displacement threat and competitive potential suggests a fundamental reshaping of how firms create and capture value. These findings not only advance our theoretical understanding of technological change but also provide actionable insights for executives and policymakers navigating the post-GenAI environment.

As GenAI continues to evolve, our research underscores the need for a dynamic, context-specific approach to both strategy formulation and policy development. The simultaneous potential for displacement and new forms of competitive advantage points to an uneven future, where some firms may thrive even as others in their sector struggle. In addition to informing strategy, our findings highlight the critical role of regulation in shaping AI adoption and impact, suggesting that policymakers must strike a delicate balance between fostering innovation and mitigating potential negative consequences. By providing an early empirical foundation for understanding these shifts, our study sets the stage for a new wave of research exploring the interplay between AI technologies, organizational capabilities, industry dynamics, and regulatory frameworks. As we stand at the cusp of what may be a new technological paradigm, the insights gleaned from this work offer a starting point for navigating the challenges and opportunities that lie ahead.

References

Abernathy WJ, Clark KB. 1985. Innovation: Mapping the winds of creative destruction. *Research Policy* **14**(1): 3–22.

Acemoglu D. 2024. *The Simple Macroeconomics of AI*. National Bureau of Economic Research, Cambridge, MA: w32487. Available at: http://www.nber.org/papers/w32487.pdf.

Acemoglu D, Autor D, Hazell J, Restrepo P. 2022. Artificial Intelligence and Jobs: Evidence from Online Vacancies. *Journal of Labor Economics* **40**(S1): S293–S340.

Acemoglu D, Restrepo P. 2018, January. Artificial Intelligence, Automation and Work. Working Paper Series. Working Paper, National Bureau of Economic Research. Available at: https://www.nber.org/papers/w24196.

Acemoglu D, Restrepo P. 2020. The wrong kind of AI? Artificial intelligence and the future of labour demand. *Cambridge Journal of Regions, Economy and Society* **13**(1): 25–35.

Achiam J *et al.* 2024, March 4. GPT-4 Technical Report. arXiv. Available at: http://arxiv.org/abs/2303.08774.

Adner R, Lieberman M. 2021. Disruption Through Complements. *Strategy Science* **6**(1): 91–109.

Agrawal A, Gans JS, Goldfarb A. 2019. Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. *Journal of Economic Perspectives* **33**(2): 31–50.

Agrawal AK, Gans J, Goldfarb A. 2021, May 1. Ai Adoption and System-Wide Change. SSRN Scholarly Paper, Rochester, NY. Available at: https://papers.ssrn.com/abstract=3847556.

Agrawal AK, Gans JS, Goldfarb A. 2018. Exploring the Impact of Artificial Intelligence: Prediction versus Judgment.

Allen R, Choudhury P (Raj). 2022. Algorithm-Augmented Work and Domain Experience: The Countervailing Forces of Ability and Aversion. *Organization Science* **33**(1): 149–169.

Anderson P, Tushman ML. 1990. Technological Discontinuities and Dominant Designs: A Cyclical Model of Technological Change. *Administrative Science Quarterly* **35**(4): 604.

Argote L, Ingram P. 2000. Knowledge Transfer: A Basis for Competitive Advantage in Firms. *Organizational Behavior and Human Decision Processes* **82**(1): 150–169.

Arthur WB. 1989. Competing Technologies, Increasing Returns, and Lock-In by Historical Events. *The Economic Journal* **99**(394): 116.

Autor DH, Dorn D. 2013. The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review* **103**(5): 1553–1597.

Balasubramanian N, Ye Y, Xu M. 2022. Substituting Human Decision-Making with Machine Learning: Implications for Organizational Learning. *Academy of Management Review*. Academy of Management **47**(3): 448–465.

Baldwin CY. 2024. *Design Rules, Volume 2: How Technology Shapes Organizations*. MIT Press, 2.

Bamberger PA. 2018. AMD—Clarifying What We Are about and Where We Are Going. *Academy of Management Discoveries* **4**(1): 1–10.

Bayus BL, Agarwal R. 2007. The Role of Pre-Entry Experience, Entry Timing, and Product Technology Strategies in Explaining Firm Survival. *Management Science*. INFORMS **53**(12): 1887–1902.

Behfar K, Okhuysen GA. 2018. Perspective—Discovery Within Validation Logic: Deliberately Surfacing, Complementing, and Substituting Abductive Reasoning in Hypothetico-Deductive Inquiry. *Organization Science*. INFORMS **29**(2): 323–340.

Benner MJ. 2007. The Incumbent Discount: Stock Market Categories and Response to Radical Technological Change. *The Academy of Management Review*. Academy of Management **32**(3): 703–720.

Benner MJ. 2010. Securities Analysts and Incumbent Response to Radical Technological Change: Evidence from Digital Photography and Internet Telephony. *Organization Science* **21**(1): 42–62.

Bessen J, Impink SM, Reichensperger L, Seamans R. 2022. The role of data for AI startup growth. *Research Policy* **51**(5): 104513.

Bessen JE, Impink SM, Reichensperger L, Seamans R. 2023, July 25. The Business of AI Startups. SSRN Scholarly Paper, Rochester, NY. Available at: https://papers.ssrn.com/abstract=3293275.

Boiko DA, MacKnight R, Gomes G. 2023. Emergent autonomous scientific research capabilities of large language models. arXiv. Available at: https://arxiv.org/abs/2304.05332.

Boussioux L, Lane JN, Zhang M, Jacimovic V, Lakhani KR. 2024. The Crowdless Future? Generative AI and Creative Problem-Solving. *Organization Science*.

Brand J, Israeli A, Ngwe D. 2023, March 21. Using LLMs for Market Research. SSRN Scholarly Paper, Rochester, NY. Available at: https://papers.ssrn.com/abstract=4395751.

Bresnahan T. 2021. Artificial Intelligence Technologies and Aggregate Growth Prospects. In *Prospects for Economic Growth in the United States*, Zodrow GR, Diamond JW (eds). Cambridge University Press: Cambridge: 132–170.

Bresnahan T. 2024. What innovation paths for AI to become a GPT? *Journal of Economics & Management Strategy* **33**(2): 305–316.

Bresnahan TF, Trajtenberg M. 1995. General purpose technologies 'Engines of growth'? *Journal of Econometrics* **65**(1): 83–108.

Brynjolfsson E, Hitt LM. 2000. Beyond Computation: Information Technology, Organizational Transformation and Business Performance. *Journal of Economic Perspectives* **14**(4): 23–48.

Brynjolfsson E, Jin W, McElheran K. 2021. The power of prediction: predictive analytics, workplace complements, and business performance. *Business Economics* **56**(4): 217–239.

Brynjolfsson E, Li D, Raymond LR. 2023, April. Generative AI at Work. Working Paper Series. Working Paper, National Bureau of Economic Research. Available at: https://www.nber.org/papers/w31161.

Brynjolfsson E, McAfee A. 2014. *The second machine age: work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company: New York London.

Brynjolfsson E, Mitchell T. 2017. What can machine learning do? Workforce implications. *Science*. American Association for the Advancement of Science **358**(6370): 1530–1534.

Bubeck S *et al.* 2023, April 13. Sparks of Artificial General Intelligence: Early experiments with GPT-4. arXiv. Available at: http://arxiv.org/abs/2303.12712.

Burström T, Parida V, Lahti T, Wincent J. 2021. AI-enabled business-model innovation and transformation in industrial ecosystems: A framework, model and outline for further research. *Journal of Business Research* **127**: 85–95.

Chan-Olmsted SM. 2019. A Review of Artificial Intelligence Adoptions in the Media Industry. *International Journal on Media Management*. Routledge **21**(3–4): 193–215.

Chari VV, Hopenhayn H. 1991. Vintage Human Capital, Growth, and the Diffusion of New Technology. *Journal of Political Economy*. University of Chicago Press **99**(6): 1142–1165.

Charmaz K. 2006. *Constructing grounded theory*, 2nd edition. Introducing qualitative methods. Sage: London; Thousand Oaks, Calif.

Choudhury P, Starr E, Agarwal R. 2020. Machine learning and human capital complementarities: Experimental evidence on bias mitigation. *Strategic Management Journal* **41**(8): 1381–1411.

Christensen CM. 1997. *The innovator's dilemma: when new technologies cause great firms to fail*. The management of innovation and change series. Harvard Business School Press: Boston, Mass.

Christensen CM, Raynor ME. 2010. *The innovator’s solution: creating and sustaining successful growth*, 14 Dr. Harvard Business School Press: Boston, Mass.

Cohen WM, Levinthal DA. 1989. Innovation and Learning: The Two Faces of R & D. *The Economic Journal* **99**(397): 569.

Cohen WM, Levinthal DA. 1990. Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*. The Johnson Graduate School, Cornell University: US **35**(1): 128–152.

Cowgill B, Tucker CE. 2020, February 14. Algorithmic Fairness and Economics. Rochester, NY. Available at: https://papers.ssrn.com/abstract=3361280.

Creswell JW, Plano Clark VL. 2018. *Designing and conducting mixed methods research*, Third edition, international student edition. Sage: Los Angeles London New Delhi Singapore Washington DC Melbourne.

Csaszar F, Ketkar H, Kim H. 2024. Artificial Intelligence and Strategic Decision-Making: Evidence from Entrepreneurs and Investors. *Working Paper*.

Csaszar FA, Steinberger T. 2022. Organizations as Artificial Intelligences: The Use of Artificial Intelligence Analogies in Organization Theory. *Academy of Management Annals* **16**(1): 1–37.

Danneels E. 2011. Trying to become a different type of company: dynamic capability at Smith Corona. *Strategic Management Journal* **32**(1): 1–31.

Davenport TH, Kirby J. 2016. Just How Smart Are Smart Machines? *MIT Sloan Management Review*. Available at: https://sloanreview.mit.edu/article/just-how-smart-are-smart-machines/.

David PA. 1990. The Dynamo and the Computer: An Historical Perspective on the Modern Productivity Paradox. *The American Economic Review*. American Economic Association **80**(2): 355–361.

Dell’Acqua F *et al.* 2023. Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality. *SSRN Electronic Journal*. Available at: https://www.ssrn.com/abstract=4573321.

Doshi AR, Hauser OP. 2023. Generative artificial intelligence enhances creativity but reduces the diversity of novel content. arXiv. Available at: https://arxiv.org/abs/2312.00506.

Eggers JP. 2014. Competing technologies and industry evolution: The benefits of making mistakes in the flat panel display industry: Competing Technologies and Industry Evolution. *Strategic Management Journal* **35**(2): 159–178.

Eggers JP, Kaplan S. 2009. Cognition and Renewal: Comparing CEO and Organizational Effects on Incumbent Adaptation to Technical Change. *Organization Science* **20**(2): 461–477.

Eggers JP, Park KF. 2018. Incumbent Adaptation to Technological Change: The Past, Present, and Future of Research on Heterogeneous Incumbent Response. *Academy of Management Annals* **12**(1): 357–389.

Furnari S *et al.* 2021. Capturing Causal Complexity: Heuristics for Configurational Theorizing. *Academy of Management Review* **46**(4): 778–799.

Gioia DA, Chittipeddi K. 1991. Sensemaking and Sensegiving in Strategic Change Initiation. *Strategic Management Journal*. Wiley **12**(6): 433–448.

Gioia DA, Corley KG, Hamilton AL. 2013. Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology. *Organizational Research Methods* **16**(1): 15–31.

Girotra K, Meincke L, Terwiesch C, Ulrich KT. 2023, July 10. Ideas are Dimes a Dozen: Large Language Models for Idea Generation in Innovation. SSRN Scholarly Paper, Rochester, NY. Available at: https://papers.ssrn.com/abstract=4526071.

Goldman Sachs. 2023. *The Potentially Large Effects of Artificial Intelligence on Economic Growth*. Goldman Sachs. Available at: https://www.gspublishing.com/content/research/en/reports/2023/03/27/d64e052b-0f6e-45d7-967b-d7be35fabd16.html.

Guba EG, Lincoln YS. 1982. Epistemological and Methodological Bases of Naturalistic Inquiry. *Educational Communication and Technology*. Springer **30**(4): 233–252.

Heckman JJ. 1979. Sample Selection Bias as a Specification Error. *Econometrica* **47**(1): 153.

Helfat CE. 2002. The birth of capabilities: market entry and the importance of pre-history. *Industrial and Corporate Change* **11**(4): 725–760.

Helfat CE, Raubitschek RS. 2018. Dynamic and integrative capabilities for profiting from innovation in digital platform-based ecosystems. *Research Policy* **47**(8): 1391–1399.

Henderson RM, Clark KB. 1990. Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms. *Administrative Science Quarterly* **35**(1): 9.

Humlum A, Vestergaard E. 2024, April 25. The Adoption of ChatGPT. Working Paper, . Available at: https://papers.ssrn.com/abstract=4807516.

Iansiti M. 2000. How the Incumbent Can Win: Managing Technological Transitions in the Semiconductor Industry. *Management Science*. INFORMS **46**(2): 169–185.

Iansiti M, Lakhani KR. 2020. *Competing in the age of AI: strategy and leadership when algorithms and networks run the world*. Harvard Business Review Press: Boston, Massachusetts.

Jacobides MG, Brusoni S, Candelon F. 2021. The Evolutionary Dynamics of the Artificial Intelligence Ecosystem. *Strategy Science* **6**(4): 412–435.

Jick TD. 1979. Mixing Qualitative and Quantitative Methods: Triangulation in Action. *Administrative Science Quarterly* **24**(4): 602–611.

Kaplan S, Tripsas M. 2008. Thinking about technology: Applying a cognitive lens to technical change. *Research Policy*. Elsevier **37**(5): 790–805.

Katz J. 2002. From How to Why: On Luminous Description and Causal Inference in Ethnography (part 2). *Ethnography*. SAGE Publications **3**(1): 63–90.

Kellogg K *et al.* 2024. Don't Expect Juniors to Teach Senior Professionals to Use Generative AI: Emerging Technology Risks and Novice AI Risk Mitigation Tactics. Available at: https://www.ssrn.com/abstract=4857373.

Kim H, Glaeser EL, Hillis A, Kominers SD, Luca M. 2024. Decision authority and the returns to algorithms. *Strategic Management Journal* **45**(4): 619–648.

Krakowski S, Luger J, Raisch S. 2023. Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal* **44**(6): 1425–1452.

Lechner C, Lang N, Handschuh S, Bouffault O, Cooper J. 2024. Can GenAI do your next strategy task? Not yet. *California Management Review Insights*. Available at: https://cmr.berkeley.edu/2024/09/can-genai-do-your-next-strategy-task-not-yet/.

Long JS, Freese J. 2006. *Regression Models for Categorical Dependent Variables using Stata, 2nd Edition*. Stata Press books, StataCorp LP. Available at: https://econpapers.repec.org/bookchap/tsjspbook/long2.htm.

Ludwig J, Mullainathan S. 2023, March. Machine Learning as a Tool for Hypothesis Generation. Working Paper Series. Working Paper, National Bureau of Economic Research. Available at: https://www.nber.org/papers/w31017.

MacDuffie JP. 2013. Modularity-as-Property, Modularization-as-Process, and 'Modularity'-as-Frame: Lessons from Product Architecture Initiatives in the Global Automotive Industry. *Global Strategy Journal* **3**(1): 8–40.

MacDuffie JP, Jacobides MG, Tae CJ. 2024. Revisiting Disruption: Lessons from Automotive and Mobility Service Innovations.

Manning BS, Zhu K, Horton JJ. 2024. Automated Social Science: Language Models as Scientist and Subjects. arXiv. Available at: https://arxiv.org/abs/2404.11794.

McElheran K *et al.* 2024. AI adoption in America: Who, what, and where. *Journal of Economics & Management Strategy* **33**(2): 375–415.

McKinsey & Co. 2023. *AI could increase corporate profits by $4.4 trillion a year, according to new research | McKinsey*. McKinsey & Co. Available at: https://www.mckinsey.com/mgi/overview/in-the-news/ai-could-increase-corporate-profits-by-4-trillion-a-year-according-to-new-research.

McKinsey & Co. 2024. *The state of AI in early 2024: Gen AI adoption spikes and starts to generate value*. McKinsey & Co. Available at: https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai.

Miles MB, Huberman AM. 1994. *Qualitative data analysis: An expanded sourcebook, 2nd ed*. Qualitative data analysis: An expanded sourcebook, 2nd ed. Sage Publications, Inc: Thousand Oaks, CA, US: xiv, 338.

Mitchell W. 1989. Whether and When? Probability and Timing of Incumbents' Entry into Emerging Industrial Subfields. *Administrative Science Quarterly* **34**(2): 208–230.

Mitchell W, Wu Z, Bruton GD, Gautam DK. 2022. Microlevel Analysis of Institutional Intermediation in a Rudimentary Market-Based Economy: Entrepreneurship in Kathmandu's Indrachok Market. *Organization Science* **33**(6): 2106–2134.

Mollick E. 2024. *Co-intelligence: living and working with AI*. Portfolio/Penguin: New York.

Murray A, Rhymer J, Sirmon DG. 2021. Humans and Technology: Forms of Conjoined Agency in Organizations. *Academy of Management Review*. Academy of Management **46**(3): 552–571.

Nederhof AJ. 1985. Methods of coping with social desirability bias: A review. *European Journal of Social Psychology*. John Wiley & Sons: US **15**(3): 263–280.

Noy S, Zhang W. 2023. Experimental evidence on the productivity effects of generative artificial intelligence. *Science* **381**(6654): 187–192.

Otis N, Clarke R, Delecourt S, Holtz D, Koning R. 2024, February 27. The Uneven Impact of Generative AI on Entrepreneurial Performance. Working Paper, Rochester, NY. Available at: https://papers.ssrn.com/abstract=4671369.

Pillai S, Gambardella A, Goldfarb B, King A. 2020. Abduction and the Problem of Null. *Academy of Management Proceedings*. Academy of Management **2020**(1): 15012.

Ployhart RE, Bartunek JM. 2019. Editors' Comments: There Is Nothing So Theoretical As Good Practice—A Call for Phenomenal Theory. *Academy of Management Review*. Academy of Management **44**(3): 493–497.

Raisch S, Krakowski S. 2021. Artificial intelligence and management: The automation–augmentation paradox. *The Academy of Management Review*. Academy of Management: US **46**(1): 192–210.

Risi S, Preuss M. 2020. From Chess and Atari to StarCraft and Beyond: How Game AI is Driving the World of AI. *KI - Künstliche Intelligenz* **34**(1): 7–17.

Rogers EM. 2003. *Diffusion of innovations*, Fifth edition, Free Press trade paperback edition. Social science. Free Press: New York London Toronto Sydney.

Rosenberg N. 1976. On Technological Expectations. *The Economic Journal*. [Royal Economic Society, Wiley] **86**(343): 523–535.

Rosenberg N. 1998. Uncertainty and Technological Change. In *The Economic Impact of Knowledge*. Routledge.

Sack D *et al.* 2024. GenAI Doesn't Just Increase Productivity. It Expands Capabilities. Available at: https://bcghendersoninstitute.com/wp-content/uploads/2024/09/gen-ai-increases-productivity-and-expands-capabilities.pdf.

Sahoh B, Choksuriwong A. 2023. The role of explainable Artificial Intelligence in high-stakes decision-making systems: a systematic review. *Journal of Ambient Intelligence and Humanized Computing* **14**(6): 7827–7843.

Sogani J, Allen B, Dreyer K, McGinty G. 2020. Artificial intelligence in radiology: the ecosystem essential to improving patient care. *Clinical Imaging* **59**(1): A3–A6.

Stokel-Walker C, Van Noorden R. 2023. What ChatGPT and generative AI mean for science. *Nature* **614**(7947): 214–216.

Suárez FF, Utterback JM. 1995. Dominant Designs and the Survival of Firms. *Strategic Management Journal*. Wiley **16**(6): 415–430.

Svanberg M, Li W, Fleming M, Goehring B, Thompson N. 2024. Beyond AI Exposure: Which Tasks are Cost-Effective to Automate with Computer Vision? *SSRN Electronic Journal*. Available at: https://www.ssrn.com/abstract=4700751.

Teece DJ. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy* **15**(6): 285–305.

Teece DJ. 2006. Reflections on “Profiting from Innovation”. *Research Policy* **35**(8): 1131–1146.

Timmermans S, Tavory I. 2012. *Abductive Analysis: Theorizing Qualitative Research*. University of Chicago Press: Chicago, IL. Available at: https://press.uchicago.edu/ucp/books/book/chicago/A/bo18785947.html.

Tripsas M. 1997. Unraveling the Process of Creative Destruction: Complementary Assets and Incumbent Survival in the Typesetter Industry. *Strategic Management Journal*. Wiley **18**: 119–142.

Tripsas M, Gavetti G. 2000. Capabilities, cognition, and inertia: evidence from digital imaging. *Strategic Management Journal* **21**(10–11): 1147–1161.

Tushman ML, Anderson P. 1986. Technological Discontinuities and Organizational Environments. *Administrative Science Quarterly* **31**(3): 439–465.

Wang L *et al.* 2024. A Survey on Large Language Model based Autonomous Agents. *Frontiers of Computer Science* **18**(6): 186345.

Wilson J, Daugherty P. 2018, July 1. Collaborative Intelligence: Humans and AI Are Joining Forces. *Harvard Business Review*.

Appendix

Appendix A: Stage 1 Roundtables Insights

A1. Insights on GenAI Adoption Patterns

Our roundtables revealed varying degrees of GenAI adoption across sectors. Initially, we encouraged participants to speak about their own sectors, rather than abstracting to others, and to focus what is *currently happening*, rather than what could happen in the future.

Our analysis identified two primary adoption patterns: top-down and bottom-up. Regulated professional services, particularly law firms, reported implementing GenAI solutions through top-down initiatives, from developing in-house models and conducting pilot studies to deploying AI solutions at localized scales and engaging with third-party, off-the-shelf solutions. Legal executives spoke of the technology's ease of deployment and its ability to complement existing practices—for instance, by reducing time spent on research or enhancing efficiency in contract review. Notably, legal executives characterized the technology primarily in terms of complementary and iterative interaction between employees and AI, emphasizing how it augmented rather than replaced human expertise.

In contrast, non-regulated professional services and media and communications sectors described a more bottom-up approach. While few firms in these sectors had established formal top-down policies on GenAI, they did acknowledge informal use. Executives from management consultancies mentioned using AI to provide initial directions for client advisory, assisting in knowledge synthesis, and generating first drafts of pitch decks. Again, these outputs served as a starting point for further refinement and analysis by humans.

Executives in media and communications, particularly PR and advertising, also reported bottom-up adoption patterns, but tended to discuss AI applications more in terms of displacement rather than complementarity. One media executive observed, "A task which previously would have taken the junior a day to do, now they just put it in ChatGPT and get it done in a few minutes." Executives expressed concern about their inability to accurately gauge the time or effort required for tasks traditionally performed by junior staff. They admitted that their interaction with AI-generated content was often limited to "proof-checking" and described challenges in distinguishing between the respective outputs of AI and humans. Executives also expressed uncertainty about how to evaluate junior staff performance and skill development in light of AI adoption.

Financial services executives reported the lowest levels of adoption, aside from personal use for tasks such as composing emails. While these executives suspected informal use among employees, they generally advocated for a more conservative approach, often citing security concerns. One banking executive cited prior security leaks that had made the bank exceptionally cautious about adopting new technologies in haste. In contrast, participants from the EdTech sector, many from smaller organizations, reported using the technology more frequently.

Appendix B: Descriptive Patterns from Survey Data

B1. Survey and Data Collection:

We administered a Qualtrics survey to director-level executives, focusing on GenAI impact and organizational strategies. Respondents were drawn from the Institute of Directors (IoD) pool, with self-selection and no exclusion criteria. To enhance data quality, we randomized survey items and offered personalized benchmarking as an incentive. Respondents were not allowed to return to their original progress, ensuring that their responses were not influenced by later questions or the opportunity to revise earlier answers.

The IoD typically conducts monthly surveys of their membership base, coordinated through the same IoD liaison we used via email. For our study, the IoD sent this as a separate survey, explicitly stating so. This approach has precedent, as the IoD has accommodated similar requests for past research projects. We pretested the survey instrument with 10 IoD members, selected to represent diverse firm sizes and sectors, through hour-long interviews. The English-language survey was distributed via email to the entire IoD membership database in February 2024, with an initial invitation and two reminders over a two-month collection period. We tested for and found no systematic differences between the three separate waves of respondents.

Of 486 total responses, 223 were fully completed, representing our main analysis sample and a 10.85% response rate from approximately 2,000 IoD members. We found no systematic differences between partial (>50% complete) and full respondents across key variables.

Additionally, we administered the survey to a select group of alumni and Executive Education students from the authors' business school, yielding 54 additional fully completed responses. Statistical tests revealed no significant differences between this supplementary sample and our main IoD sample. All the results in our paper are also checked with the merged sample.

Table B1. Descriptive statistics of survey data

	Mean	Std. Dev.	Min	Max
Sector	12.054	4.099	1	20
Employee Numbers	3.360	1.565	1	6
Firm Annual Turnover	2.68	1.471	1	5
Technology Adoption Attitude	2.381	.767	1	3
Regulatory Intensity	3.574	1.041	1	5
GenAI Industry Expectation	3.824	1.02	1	5
GenAI Organizational Usage	2.502	.99	1	4
Barriers: Output Accuracy	3.278	1.16	1	5
Barriers: Leadership Disinterest	2.139	1.075	1	5
Barriers: IP Concern	2.874	1.16	1	5
Barriers: Financial Investment	2.641	1.051	1	5
Barriers: Strategic Uncertainty	2.704	1.028	1	5
Barriers: Staffing	2.906	1.129	1	5
Barriers: Security Compliance	3.04	1.206	1	5
Competitive Imitation	2.996	1.195	1	5
Supplier Disintermediation	3.148	1.147	1	5
Overcome Knowledge Barriers	3.049	1.136	1	5
Customer Disintermediation	3.269	1.226	1	5
Proprietary Data	3.704	1.209	1	5
Modularity	2.079	.674	1	3
Potential for Distinctiveness	5.296	1.383	1	7
Tacit Knowledge	4.35	.79	1	5
Relational Knowledge	4.457	.837	1	5
Importance of Referrals	4.036	1.114	1	5
Technical Knowledge	4.287	.914	1	5
Market Insight	4.121	.915	1	5
Pattern Recognition	3.614	1.149	1	5
Importance of Certification	3.538	1.423	1	5
Recruitment Challenges	2.668	1.207	1	5
Training Challenges	3.377	1.108	1	5
Financial Viability Challenges	3.547	1.042	1	5
AI Regulation Clarity	3.525	1.094	1	2
Industry Profit Pool Impact	3.554	.869	1	5

Note: summarizes demographics and responses for the 217 executives included in our analyses.

The survey targeted executives at director level and above, with 29.60% of respondents being CXO / president of their firm and 45.74% at director level. All respondents confirmed their executive-level status in response to a survey question. As respondents had stated their names and firms in an early survey question, we were also able to use LinkedIn to verify the status and company of each respondent.

Table B1 reports the descriptive statistics from our survey data.

B2. Descriptive Patterns: The impact of Generative AI within organizations thus far

Table B2 reports executives' assessments of GenAI's impact within their organizations thus far. This analysis serves to establish a baseline understanding of GenAI adoption patterns in our sample. When asked to describe GenAI's impact within their organization to date, 72.81% of respondents report some level of impact already. However, only 22.12% indicate significant or transformative effects, with just 7.83% reporting transformative impacts.

Table B2. Assessments of GenAI impact thus far within organizations

	GenAI impact within your organization thus far[a]				
	No impact yet	Minor impact	Moderate impact	Significant impact	Transformative impact
Total	27.19%	30.41%	20.28%	14.29%	7.83%
Small firms[b]	24.77%	23.85%	22.02%	18.35%	11.01%
Medium firms	32.35%	33.82%	19.12%	10.29%	4.41%
Large firms	23.08%	43.59%	17.95%	10.26%	5.31%
Low reg[c]	28.13%	34.38%	15.63%	12.50%	9.38%
Medium reg	31.25%	29.69%	20.31%	15.63%	3.13%
High reg	24.79%	29.75%	21.49%	14.05%	9.92%
Low modular[d]	41.46%	26.83%	17.07%	9.76%	4.88%
Medium modular	20.00%	37.39%	22.61%	13.91%	6.09%
High modular	28.57%	17.86%	19.64%	19.64%	14.29%

[a] Responses to Q24 ("Which of the following best describes Generative AI impact within your organization so far?").
[b] Responses to Q4 ("Roughly what is the annual turnover of your organization?"). Small firms are coded as up to £2M, medium firms as between £2M and £50M, large firms as above £50M.
[c] Responses to Q9 ("What is the level of regulation in your industry?"). Low regulation is coded as none to low regulation, medium regulation as medium, and high regulation as high to extreme regulation.
[d] Responses to Q20 ("How modular do you consider your business operations to be?").

Our Stage 1 roundtables suggested that firm size is positively associated with organizational rigidities (Staw, Sandelands, and Dutton, 1981), with smaller firms potentially benefiting from lower deployment complexity. The survey data aligns with this perspective. While small firms show similar levels of initial engagement to large firms (75.23% of small firms reporting at least minor impact compared to 76.92% of large firms), small firms are more than twice as likely, in terms of sample representation, to experience transformative impacts (11.01% vs. 5.31% for large firms).

The Stage 1 roundtables highlighted differences in GenAI impact that appeared to co-vary with regulatory intensity across sectors. Our survey data revealed a more nuanced relationship here. While we don't observe significant differences for overall positive experiences with GenAI across regulatory intensities, high-regulation firms and low regulation firms show significantly higher likelihood, in terms of sample representation, of experiencing transformative impacts compared to medium-regulation firms (9.92% and 9.38% vs. 3.13%).

Organizational modularity emerged as a key enabler for deploying GenAI in our initial roundtables. Our descriptive data strongly aligns with this observation. High-modularity organizations report significant or transformative AI impacts at more than double the rate of low-modularity firms (14.29% vs. 4.88%), showing a stark contrast in adoption experiences.

This baseline assessment of current GenAI impact provides a useful foundation for understanding the state of GenAI adoption thus far and serves as a relevant exercise in sense-checking some of the key insights from our Stage 1 roundtables.

B3. Descriptive Patterns: GenAI expectations on organization and industry

Building on our baseline assessment of current GenAI impact, we now turn to executives' expectations for GenAI's future influence both within their organizations and across their industries.

Table B3 presents expectations for GenAI within respondents' own organizations. Notably, 84.75% of executives anticipate some meaningful change, with 40.36% expecting operational efficiency gains, 23.32% foreseeing strategic transformation, and 21.08% predicting business-model reinvention. In contrast, Table B4 shows expectations for GenAI's importance within the broader industry, revealing a markedly more bullish outlook. Here, 89.19% of respondents view GenAI as at least moderately important to their industry's future, with 64.86% considering it very or extremely important.

Table B3. Expectations of GenAI's impact within organizations

	GenAI's expected impact within your organization[a]			
	No meaningful change	Operational efficiency	Strategic transformation	Business-model reinvention
Total	15.25%	40.36%	23.32%	21.08%
Small firms[b]	16.81%	32.74%	23.01%	27.43%
Medium firms	18.57%	45.71%	20.00%	15.71%
Large firms	5.13%	53.85%	28.21%	12.82%
Low reg[c]	31.25%	28.13%	21.88%	18.75%
Medium reg	18.46%	38.46%	21.54%	21.54%
High reg	9.52%	44.44%	24.60%	21.43%

[a] Responses to Q11 ("Which of the following best describes the level of overall Generative AI expectation within your organization?")
[b] Responses to Q4 ("Roughly what is the annual turnover of your organization?"). Small firms are defined as up to £2M, medium firms as between £2M and £50M, large firms as above £50M.
[c] Responses to Q9 ("What is the level of regulation in your industry?"). Low regulation is defined as none to low regulation, medium regulation as medium, and high regulation as high to extreme regulation.

This discrepancy between organizational and industry expectations presents an intriguing puzzle: *Why do executives appear more optimistic about AI's transformative potential at the industry level compared to within their own organizations?* This divergence might suggest that executives perceive ways in which GenAI can be leveraged by certain organizations within the industry, while simultaneously recognizing significant barriers within their own organizations. It could reflect a nuanced understanding of AI's disruptive force coupled with a realistic assessment of the challenges in harnessing it effectively within specific organizational contexts.

Table B4. Expectations of GenAI's impact within industries

	GenAI's expected impact within your industry[a]				
	Not at all important	Slightly important	Moderately important	Very important	Extremely important
Total	1.80%	9.01%	24.32%	34.68%	30.18%
Small firms[b]	2.65%	7.96%	19.47%	31.86%	38.05%
Medium firms	1.43%	14.29%	28.57%	32.86%	22.86%
Large firms	0.00%	2.56%	30.77%	46.15%	20.51%
Low reg[c]	6.25%	15.63%	21.88%	25.00%	31.25%
Medium reg	1.56%	10.94%	29.69%	32.81%	25.00%
High reg	0.79%	6.35%	22.22%	38.10%	32.54%

[a] Responses to Q12 ("How important do you perceive the usage of Generative AI to be within your industry within the next 5 years?").
[b] Responses to Q4 ("Roughly what is the annual turnover of your organization?"). Small firms are defined as up to £2M, medium firms as between £2M and £50M, large firms as above £50M.
[c] Responses to Q9 ("What is the level of regulation in your industry?"). Low regulation is defined as none to low regulation, medium regulation as medium, and high regulation as high to extreme regulation.

Our descriptive data on firm characteristics provide further insights into this puzzle. Large firms, for instance, show the highest expectations for operational efficiency gains (53.85%) but the lowest for business-model reinvention (12.82%). This aligns with observations from our Stage 1 roundtables, which identified higher barriers to transformative change in larger organizations due to legacy systems and organizational complexity. Conversely, small firms report the highest expectations for business-model reinvention (27.43%), suggesting they may perceive fewer internal barriers to appropriating value from GenAI.

B4. Descriptive Patterns: Unbundling threat of imitation and distinctiveness potential

Building on the puzzle identified above—the discrepancy between high industry-level expectations for GenAI and more modest organizational-level predictions—we now examine executives' assessments of GenAI's potential to unlock distinctiveness and its effect on competitive imitation. These two dimensions offer insight into how executives perceive GenAI's role in both creating and potentially eroding competitive advantage, which may help to explain the observed expectation gap.

Tables B5 and B6 reveal contrasting distributional properties in these assessments. Table B5 shows a clear positive skew in perceptions of GenAI's potential to unlock distinctiveness, with

91.93% of the sampled executives seeing at least some positive potential. The distribution is unimodal, with a peak in the "slight positive" category (30.94%) and a substantial right tail extending to "extreme positive" (19.28%). Conversely, only 8.07% of our entire sample reported that they believed their distinctiveness would be eroded by GenAI.

Table B5. Assessments of the potential to unlock distinctiveness through GenAI

	Potential to unlock distinctiveness[a]						
	Extreme negative	Moderate negative	Slight negative	Neutral	Slight positive	Moderate positive	Extreme positive
Total	2.69%	3.14%	2.24%	13.00%	30.94%	28.70%	19.28%
Small firms[b]	4.42%	0.88%	1.77%	11.50%	28.32%	29.20%	23.89%
Medium firms	1.43%	4.29%	2.86%	17.14%	34.29%	24.29%	15.71%
Large firms	0.00%	7.69%	2.56%	10.26%	33.33%	33.33%	12.82%
Low reg[c]	12.50%	0.00%	3.33%	21.88%	15.63%	31.25%	15.63%
Medium reg	3.08%	3.08%	3.08%	9.23%	41.54%	27.69%	12.31%
High reg	0.00%	3.97%	1.59%	12.70%	29.37%	28.57%	23.81%

[a] Responses to Q26 ("Assess the potential for Generative AI to unlock new opportunities for distinctiveness within your market").
[b] Responses to Q4 ("Roughly what is the annual turnover of your organization?"). Small firms are defined as up to £2M, medium firms as between £2M and £50M, large firms as above £50M.
[c] Responses to Q9 ("What is the level of regulation in your industry?"). Low regulation is defined as none to low regulation, medium regulation as medium, and high regulation as high to extreme regulation.

In contrast, Table B6 presents a more uniform distribution regarding GenAI's impact on competitive imitation. The data show a bimodal tendency, with peaks at both ends of the spectrum: 37.66% viewing imitation as becoming easier following GenAI, and 34.52% viewing imitation as becoming more difficult. This balanced distribution differs markedly from the skewed distribution observed for distinctiveness potential.

Table B6. Assessments of the effect of GenAI on the ease of competitive imitation

	Ease of competitive imitation following GenAI[a]				
	Extremely easy	Somewhat easy	Neither easy nor difficult	Somewhat difficult	Extremely difficult
Total	10.31%	27.35%	27.80%	21.52%	13.00%
Small firms[b]	11.50%	29.20%	23.89%	23.01%	12.39%
Medium firms	10.00%	21.43%	28.57%	22.86%	17.14%
Large firms	7.69%	33.33%	35.90%	15.38%	7.69%
Low reg[c]	9.38%	25.00%	28.13%	9.38%	28.13%
Medium reg	10.77%	21.54%	26.15%	32.31%	9.23%
High reg	10.32%	30.95%	28.57%	19.05%	11.11%

[a] Responses to Q14 (“If Generative AI spreads widely in your industry, how easy/difficult do you think it would be for your competitors to directly imitate your products/services”).
[b] Responses to Q4 (“Roughly what is the annual turnover of your organization?”). Small firms are defined as up to £2M, medium firms as between £2M and £50M, large firms as above £50M.
[c] Responses to Q9 (“What is the level of regulation in your industry?”). Low regulation is defined as none to low regulation, medium regulation as medium, and high regulation as high to extreme regulation.

These differing distributional properties suggest that the factors influencing perceptions of AI-driven distinctiveness may be distinct from those shaping views on GenAI-facilitated imitation. This distinction becomes more apparent when examining the data across organizational characteristics.

Firm size appears to influence these perceptions significantly. Smaller firms demonstrate the most optimism about GenAI's potential to unlock distinctiveness, with 81.41% seeing positive potential and 23.89% reporting "extreme positive" expectations. However, they also perceive the highest threat of imitation, with 40.70% viewing it as easier. In contrast, larger firms show more conservative assessments in both dimensions, suggesting that existing resources and market position may buffer both the opportunities and threats posed by GenAI.

The regulatory environment also plays a role in shaping perspectives. Firms in highly regulated environments are most optimistic about GenAI's potential to unlock distinctiveness (81.75% positive) but also perceive the greatest threat of imitation (41.27% viewing it as easier).

These contrasting distributional properties and their variations across organizational characteristics suggest that different sets of variables may be associated with GenAI’s perceived ability to create differentiation and its potential to facilitate imitation. The factors that relate to perceptions of GenAI-driven competitive advantage appear to differ from those linked to concerns about GenAI-driven imitation, potentially contributing to the complex landscape of executive expectations for GenAI’s strategic impact.

Appendix C: Ordinal Logistic Regression Analyses

C1. Context and Methodology

Descriptive statistics from the survey reinforce key insights from the Stage 1 qualitative roundtables. Executives' assessments of GenAI's impact and potential vary significantly across organizational characteristics and strategic factors. The data reveal a notable discrepancy between expectations for AI's transformative potential at the industry level compared to within respondents' own organizations.

The contrasting distributional properties observed in perceptions of GenAI-driven distinctiveness and competitive imitation indicate that different sets of variables may be associated with these two dimensions of GenAI's impact. The factors influencing views on GenAI's potential to create differentiation appear distinct from those shaping concerns on GenAI-facilitated displacement.

Ordinary least squares (OLS) regression is inappropriate for analyzing relationships between ordinal variables due to its violation of key assumptions, e.g., the continuity and unboundedness of the dependent variable, the equal interval property, and the normality of residuals. These violations can lead to biased estimates and coefficient misinterpretation. As a more viable and commonly used alternative, ordinal logistic regression (OLR) models were used to examine factors associated with executives' perceptions of GenAI's disruptive potential. OLR models are appropriate for our study as our variables have a natural ordering. OLR preserves this ordering and allows for non-linear relationships between independent variables and ordinal outcomes, hence more suitable than alternatives such as multinomial logistic regression (Long and Freese, 2006).

A critical assumption underlying OLR is the proportional odds assumption, where the relationship between each pair of outcome groups is assumed to be the same. In other words, the coefficients describing the relationship between the lowest versus all higher categories of the response variable are not statistically different to those describing the relationship between the next lowest category and all higher categories, and so on. We tested this assumption for each of our models using likelihood ratio tests and Brant tests. Our analyses revealed no significant violations of the proportional odds assumption, with detailed statistical results presented in subsequent sections. We estimated three models for each set of dependent variables to analyze barriers to, and enablers of, GenAI adoption and expectations.

C2. OLR Results (GenAI Experiences vs. Expectations)

In the commentary on descriptive patterns in the main study and Appendix B, we noted that executives appear more optimistic about GenAI's transformative potential at the industry level compared to within their own organizations. Our OLR results align with this perspective, suggesting that respondents perceive a set of barriers that they believe are not necessarily affecting all the organizations in their sectors, as evidenced by variables gaining and losing significance across different dependent variables.

Table C1 reports results for barrier models, aligning with our Stage 1 roundtable findings. The varying significance of variables across models of current organizational impact (proportional odds test p = 0.455), expected organizational impact (proportional odds test p = 0.6408), and expected industry impact (proportional odds test p = 0.074) supports our proposition that executives recognize GenAI's potential for certain organizations within the industry, while acknowledging significant barriers within their own.

Table C1. OLR models predicting relevance of Stage 1 barriers

	Existing organizational impact of GenAI	Expectation of GenAI organizational impact	Expectation of GenAI industry impact
Firm size (turnover)	0.825 (0.079) [.043]	0.816 (0.081) [.040]	0.822 (0.081) [.047]
Regulation	1.286 (0.175) [.064]	1.367 (0.195) [.028]	1.531 (0.223) [.003]
Modularity	1.350 (0.273) [.139]	2.028 (0.421) [.001]	1.841 (0.388) [.004]
Output accuracy	0.922 (0.126) [.552]	0.975 (0.136) [.854]	1.062 (0.146) [.660]
Leadership disinterest	0.740 (0.103) [.030]	0.431 (0.064) [.000]	0.647 (0.088) [.001]
IP concerns	1.185 (0.155) [.193]	1.232 (0.169) [.128]	1.098 (0.148) [.489]
Financial cost	0.736 (0.110) [.041]	0.774 (0.122) [.105]	0.905 (0.138) [.512]
Strategic uncertainty	1.244 (0.204) [.185]	1.115 (0.189) [.523]	0.951 (0.155) [.759]
Staffing	0.911 (0.128) [.509]	1.540 (0.239) [.005]	1.167 (0.174) [.300]
Compliance	0.770 (0.099) [.042]	0.996 (0.135) [.977]	0.828 (0.110) [.156]
LRχ^2	31.09 [.000]	60.24 [.000]	36.62 [.000]
Pseudo R^2	0.048	0.107	0.064
Observations	211	215	215

Note: Coefficients reported in odds ratios. Robust standard errors in parentheses. p-Values are included in square brackets.

For instance, modularity significantly predicts expected organizational impact (OR = 2.028, p = .001) and industry impact (OR = 1.841, p = .004), but not current organizational impact. This suggests that while organizational flexibility may be crucial for future GenAI adoption, executives perceive it as a barrier that has yet to be overcome in their current operations. On the other hand, leadership disinterest inversely predicts current organizational impact (OR =

0.740, p = .030), expected organizational impact (OR = 0.431, p = .000), and expected industry impact (OR = 0.647, p = .001).

C3. OLR Results (Unlocking Distinctiveness vs. Threat of Imitation)

In our descriptive findings, we also observed that different sets of variables appear to affect the threat of competitive imitation versus the potential to unlock new forms of distinctiveness. Table C2, which presents enabler models focusing on expectations for GenAI's potential to create distinctiveness (proportional odds test p = 0.139), threat of competitive imitation (proportional odds test p = 0.289), and expectation of GenAI's impact in industry (proportional odds test p = 0.089). Our results here provide further evidence for this observation.

Table C2. OLR models predicting relevance of Stage 1 enablers

	Potential for GenAI Distinctiveness	Threat of Competitive Imitation	Impact of GenAI in Industry
Firm size (turnover)	0.780 (0.071) [.006]	1.074 (0.097) [.429]	0.804 (0.076) [.020]
Regulation	1.198 (0.162) [.182]	0.891 (0.116) [.376]	1.279 (0.182) [.083]
Modularity	1.046 (0.214) [.827]	0.839 (0.171) [.388]	1.537 (0.330) [.045]
Proprietary data	1.307 (0.161) [.030]	0.825 (0.100) [.113]	1.135 (0.320) [.320]
Technical knowledge	1.070 (0.178) [.685]	0.977 (0.159) [.885]	1.166 (0.201) [.374]
Tacit knowledge	1.454 (0.301) [.071]	1.178 (0.246) [.432]	1.081 (0.223) [.705]
Pattern recognition	1.510 (0.195) [.001]	1.045 (0.129) [.719]	1.293 (0.170) [.051]
Market insight	1.334 (0.232) [.097]	0.810 (0.134) [.204]	1.304 (0.227) [.126]
Relational knowledge	0.553 (0.108) [.002]	0.837 (0.154) [.334]	1.087 (0.204) [.655]
LRχ^2	52.56 [.000]	11.61 [.236]	42.56 [.000]
Pseudo R^2	0.077	0.018	0.075
Observations	215	215	215

Note: Coefficients reported in odds ratios. Robust standard errors in parentheses. p-Values are included in square brackets.

Our OLR results suggest empirical support for our initial observations. Stage 1 enablers show limited statistical associations with competitive imitation threat. However, these enablers demonstrate significant relationships with GenAI distinctiveness potential. Proprietary data and pattern-recognition capabilities emerge as robust predictors across specifications, particularly for distinctiveness potential. A one-unit increase in proprietary data importance corresponds to a 1.307 increase in log-odds of perceiving greater GenAI distinctiveness potential ($p = .030$). Pattern recognition exhibits similar positive associations for distinctiveness ($OR = 1.510$, $p = .001$) and industry impact expectations ($OR = 1.293$, $p = .051$).

Additionally, the importance of relational knowledge to firm success is inversely related to GenAI distinctiveness potential ($OR = 0.553$, $p = .002$). Market insight shows a positive association, albeit with weaker statistical significance ($OR = 1.334$, $p = .097$).

These findings corroborate our earlier propositions regarding the differential factors influencing competitive imitation threat and distinctiveness potential in the context of GenAI adoption.

Appendix D: Stage 3 Analysis

D1. Details of Stage 3 Analysis

While our manuscript presents the main insights from Stage 3, here we elaborate on how we derived these findings. We outline key factors associated with (1) perceived threat of displacement from GenAI, (2) ability to leverage GenAI for competitive advantage, and (3) expectations of overall industry disruption. Each section provides insights supported by illustrative quotes from participants.

Part 1: Factors Associated with Perceived Threat of Displacement

Our analysis revealed four key factors that executives associated with the perceived threat of displacement from GenAI: regulatory barriers, sectoral conservatism, relational capital, and reliance on technical knowledge.

Regulatory barriers

Regulatory barriers emerged as a significant factor, with executives in more highly regulated industries consistently reporting a lower perceived threat of displacement. Regulatory hurdles were seen as providing a breathing space to experiment with and adapt to GenAI:

A2a (banking): We [in financial services] will test everything because we are regulated. And there are a couple of bottlenecks. […] So, one, of course, is the AI regulation itself. How would FSFCA, who regulates us, see it? They have not defined it yet. […] I think there's not one regulation where we can talk and find things. […] Of course, the big tech companies don't like it because they've been asked now to go basically submit everything so that we can validate. […] They don't want to extract things and run through it because they want to push it to us.

A2a (technology firm): I used to be a regulator […] Both of those bodies are very much trying to encourage the adoption of wider fintech and regtech products […] But obviously […] they cannot give any sort of definitive view to industry to say, 'Use this product.' […] Clearly, it wouldn't be appropriate for an authority to endorse a product like that. But industry […] appears to be nervous of taking on any sort of product without that level of endorsement, which they're not going to get.

Executives in highly regulated sectors reported encountering "overexcitement" about GenAI from management consultancies, with these firms apparently advocating for AI applications that conflict with regulatory constraints on consulting services:

A2a (financial services): I think some other consulting firms, [consulting firm], for example, they're just pushing […] [Consulting firm] is busy here trying to get more business. Get that reporting. But they are basically saying that [we can offer] advisory by robots. Robo-advisory and stuff like that. But this falls under a regulatory grey area, maybe even a dark one.

The same executive highlighted the critical role of legal liability in their firm's service provision, underscoring why the threat of AI displacement is limited in highly regulated sectors:

A2a (financial services): Technically, even humans as brokers, we are not allowed to advise. We can recommend or we can provide information. […] And now, not a human, you ask an avatar who is picking up 20 tons of information from the dark web and giving advice […] And you buy it. And you lose all your money. Who is responsible? This is a huge issue.

These findings suggest regulatory barriers create significant obstacles for new entrants—even those with advanced Gen AI tools. They also highlight potential misunderstanding or misrepresentation of guidelines in the rush to adopt or sell Gen AI solutions.

Sectoral conservatism

Executives from more conservative sectors consistently reported a lower perceived threat, citing industry norms and inherent sector characteristics as barriers to AI adoption and new entrant threat. Explanations comprised both cultural norms towards technology (DiMaggio and Powell, 1983) and inherent requirements for output accuracy. One executive highlighted the stark contrast in adoption readiness between financial services and pharmaceuticals:

A1a (pharmaceutical firm): Well, I'm a big advocate for [GenAI]. But I'm also open to kind of uncertainties, but you can imagine that other people in the healthcare sector might be quite conservative […] The pharmaceutical and life sciences industries are extremely conservative. When I moved from the financial sector to life sciences, it felt like stepping back a century […] Although there are improvements, the sector remains very sluggish to change.

Another executive in the same sector elaborated on the cultural aspect of this conservatism:

A1b (financial services): I think there is […] a culture around fear of the new technology and what it means. And perhaps there's not enough understanding […] of the impacts or the implications [either] […] But I do believe that those who use it, who actually take the risk […] might have an advantage against [their] competitors.

Beyond cultural norms, inherent sector requirements, particularly the need for high output accuracy as an end product or service, played a crucial role in shaping AI adoption readiness. One executive contrasted low- and high-output-accuracy professional services:

A3a (healthcare consultancy): Having an advertising campaign that's a bit off is one kind of risk. But having a bridge that is a bit off, or receiving [inaccurate] advice on your health? That is a completely different story altogether. […] In these industries, precision is paramount and even minor mistakes can have serious consequences.

A2a (financial services): When it comes to perhaps in the reality of the stats, financial services, for example, is not picking up on it. Financials need precision and AI has a habit of being drastically wrong a lot of the time. That might be accurate if you want something between 1 and a million. But if you want something that is between 1 and 1.1—no, it's not good enough.

Another executive in insurance highlighted the importance of trust and human interaction:

A2a (insurance): Do you think I'm going to buy and invest my money based on just consulting AI? […] I would still go out and look for a person to give me good advice […] Not because the AI is better than the humans—maybe the humans are the same—but because it's a person I trust.

These observations underscore how sectors requiring high precision, reliability, and human trust may perceive themselves as more resistant to Gen AI displacement due to the potential risks associated with errors or lack of personal interaction.

Relational capital

Executives who rated relational capital as vital to their business success generally perceived a lower threat of displacement. This relationship was generally endogenous, as sectors where relational capital is crucial, such as strategy consulting or professional services, are systematically more prone to quality screening issues (Akerlof, 1970) and rely on mechanisms such as referrals and status (Podolny, 1993, 1994) to mitigate information asymmetries.

Many executives believed that the advent of GenAI would likely intensify these dynamics, further cementing the importance of relational capital as a buffer against displacement:

A2a (restructuring): I come from a very knowledge-based […] professional service in my life, IT service most of my life. […] Where a lot of your work is very much around, you know, knowledge, data, content. […] So, I think in many of those industries, operational efficiency, over time as people are learning, will lead to massive initial transformations because costs will come down significantly and people will be able to use their time on more human-type relationship areas of focus.

Technical knowledge

Technical knowledge, defined as expertise typically acquired through formal education and training (Kogut and Zander, 1992), has long been a key differentiator and entry barrier for many industries (Breschi, Malerba, and Orsenigo, 2000; Winter, 1984). However, executives from sectors heavily reliant on technical knowledge consistently reported a greater perceived threat of displacement from GenAI—particularly in technology-intensive sectors:

A1a (engineering consultancy): […] our industry is all about the application of technical knowledge […] I think the big fear, and it is a fear that we have as an SME, is that for the bigger and larger companies, they may be able to leverage AI […] and render us useless as such, and there is a concern about that […].

A1a (financial services): Technical knowledge, I think, is more like a multi-step, everyone will know, everyone will learn, everyone will read. So, I don't think that's going to make any difference anymore.

A1a (professional services): If your business still relies on technical knowledge, then you're toast, basically. We don't see any benefit, frankly, in trying to hang on to technical knowledge nowadays. It is no longer a differentiator and won't distinguish your business in any way, shape, or form.

Roundtable discussions also pointed to shifting areas of potential competitive advantage. Certain executives in technical knowledge-oriented firms demonstrated a more nuanced understanding of the impact of GenAI. For instance, an executive from a meteorology firm specified business functions that were susceptible to displacement and those that were not:

A3b (meteorology firm): The hierarchy of firms is going to shift in our industry for sure. Those firms with technical expertise and sophisticated digital infrastructure are going to realize their differentiation has been gone […]. We're not going to be completely substituted, we [humans] are still needed to manage statistical chaos […] Differentiation is going to more likely center around who best manages this chaos.

In B roundtables, executives referenced the concurrent repositioning that has already begun to influence organizational strategies, including the outsourcing of technical-knowledge functions:

B1 (professional services): On the technical knowledge piece […] there's been more and more contracting out to specialist organizations. So, I don't think any of us probably appreciate what the balance is between in-house versus out-of-house, as it were.

Part 2: Factors Associated with Leveraging GenAI for Competitive Advantage

Our analysis identified four key factors associated with the ability to leverage GenAI for competitive advantage: proprietary data, data cleanliness, tacit knowledge, and organizational flexibility to experiment.

Proprietary data

In both Stage 1 and Stage 2, our analysis revealed a positive association between executives' valuation of proprietary data and their anticipated ability to create differentiation through GenAI applications. The mechanism underlying this relationship appears to operate through two primary channels. First, proprietary data can be used to fine-tune generic AI models, creating bespoke solutions that outperform general-purpose models in specific domains. This allows firms to develop AI applications that are more accurate and relevant to their specific business contexts. Second, combining proprietary data with GenAI's pattern-recognition capabilities can yield novel insights unavailable to competitors, leading to new business opportunities or process optimization. These mechanisms are salient in sectors characterized by complex, specialized information:

B2 (law firm): Collaborations between pharma companies on developing a vaccine involve a lot of intellectual property, licenses, and terms. […] To illustrate the point, imagine two law firms who have completed French nuclear energy projects. They have to navigate planning laws, indemnities, liability allocation, supply chain issues, government funding, and other external funding. But you can't just put that into ChatGPT and get an answer to draft a French nuclear energy contract. It's impossible, because the system isn't trained on that specific data, which likely exists only in a few cloud-based files. That data is intellectual property—it's incredibly valuable, high-end, and rare. And we have billions of such valuable data points all over the world.

Many executives, especially at professional services firms, reported a realization that their firms possess vast proprietary data reservoirs with underappreciated potential following GenAI:

B2 (consulting firm): We've been collecting data from thousands of client engagements over decades, but we've barely scratched the surface of what insights we might unlock. With generative AI, we're beginning to see our historical data in a new light. […] We're certain there's immense value hidden in our data that could revolutionize how we serve our clients.

B2 (professional services): If I take the world of, you know, financial diligence, which we are probably the world number one in doing, we have done more financial diligence exercises than almost anybody else put together. We know how to do that. We've got the historical data. We've got the metrics and we've got a bench strength of thousands of people who can help effectively train a model to do that.

Data cleanliness

Executives also perceived data cleanliness—the quality, accessibility, and usability of data—as a distinct and critical factor in firms' ability to leverage GenAI. One professional services executive even expressed that the cleanliness of proprietary data was a more unique capability than the data itself. Other managers concurred:

A2a (restructuring): Financial services typically will have enough data anyway. It's just a matter of whether the data is clean enough […] that enables you to build a model that understands the different types of data and can be fine-tuned on that data.

A1a (technology firm): We have all this proprietary data that's incredibly valuable, but accessing it is a nightmare. The effort to merge and clean the data is enormous, and we're not even sure if we can do it successfully.

This issue was pronounced in sectors with complex legacy systems and regulatory constraints:

A2a (financial services): Data itself is a huge issue for our industry. Huge controversies. We still can't have a 360º view of our customers. Data is [spread] across thousands and hundreds of systems, especially in the insurance sector.

A2a (financial services): The perception of the businesses is, 'My data is my data.' That's a competitive advantage against anything else. And I've done this [data sharing] for the last 20 years and it has not worked. […] Because if Allianz is having a claim and VWare is having a claim from the same policyholder, you just can't find fraud. And they would never mix the data. […] We spent billions to upgrade that […] We can't do anything with that system other than just storing data. So, it's very hard.

In legal services, client confidentiality rules add another layer of complexity:

B1 (law firm): We're sitting on a goldmine of data, but much of it is protected by client confidentiality rules. It's a Catch-22. We can't bring in outside help to clean and organize our data, which slows us down. But it also protects us from big tech companies swooping in to acquire our data. We have to solve this puzzle internally, which is challenging but could ultimately be key.

Tacit knowledge

Tacit knowledge, defined as implicit know-how and expertise that is difficult to codify or transfer (Polanyi, 1966), emerged as a significant factor throughout all three stages. Executives who rated tacit knowledge as vital to their business success consistently expressed greater optimism about leveraging GenAI for competitive advantage. This suggests a complementary relationship driven by the potential for tacit knowledge to guide the effective application and interpretation of AI-generated outputs:

A2b (construction): In our sector, tacit knowledge is the intricacies behind building a wall and then plastering it. Expert plasterers know exactly what they're doing, and it's quite difficult to replicate that with a machine, though we can do it with brickwork. There comes a point when perhaps we'll be able to do it with plaster as well […] Our expectation is that we have the people with the best understanding of these tacit features and hence will be able to use generative AI better than others.

This complementarity manifests in (1) the ability to frame problems and queries in ways that leverage AI capabilities effectively, and (2) the capacity to interpret and contextualize AI outputs within specific business contexts.

Executives, especially those in industries with apprenticeship traditions, expressed concern that GenAI's substitution of traditional tasks could hinder tacit knowledge development.

A1b (consulting firm): Take presentation-making, for example. It's a skill we have to train our juniors into what makes a compelling presentation. […] Now, with AI potentially taking over these tasks, we're worried about how our juniors will develop that critical eye, that intuition for what works.

This observation highlights a paradox: while tacit knowledge is seen as crucial for leveraging GenAI, the technology itself may be disrupting traditional pathways for developing such knowledge, as human judgement and intuition potentially atrophy in areas where AI takes over routine tasks.

B2 participants highlighted not only the scarcity of human capital possessing tacit knowledge but also the inherent challenges in codifying certain processes:

B2 (manufacturing): The challenge is, do we even know exactly what is our capacity? […] Basically, the simple question of what it would take to deliver this project in a codifiable manner […] I'm afraid we don't have that. […] So, I feel like there's a bit of a catch-up that is needed […].

Organizational flexibility to experiment

Organizational flexibility to experiment, defined as a firm's capacity to freely explore and test new technologies and processes, encompasses a willingness to take calculated risks, allocate resources to unproven initiatives, and learn from both successes and failures.

Our analysis revealed significant heterogeneity in this capability, even among firms within the same sector:

A3b (meteorology firm): Yeah, the possible reaping of benefits […] China seeds clouds in order to prevent droughts […] You need a pretty good forecast, and that's something where AI could help a lot. […] So, things like that where people are willing to do something slightly outside of the norm to reap the benefits of the forecast. […] I think it will accelerate those changing dynamics.

This quote demonstrates how organizational flexibility can enable high-stakes experimentation with emerging technologies, potentially yielding significant benefits but also carrying substantial risks. The ability to navigate these trade-offs appears to be a key differentiator in how firms approach GenAI adoption.

Executives emphasized that this flexibility to experiment cannot be developed overnight; rather, it was generally described as a structural pre-adaptation. SpaceX and Elon Musk were frequently cited as exemplars of organizational flexibility to experiment, with executives noting that certain organizations or leaders have stakeholders who are more accepting of risk-taking, allowing for greater experimentation even within traditionally conservative sectors:

B2 (technology firm): As long as the entire system is stuck with all of these processes and procedures that they implemented years ago, so finally, there is also a big barrier that we cannot properly enter into it because as long as this [new technology] provider doesn't [provide any backward compatibility], then you're stuck with the [old] system.

This perspective was further reinforced by a long-serving director in manufacturing:

A3a (manufacturing): The ability to experiment freely with new technologies like AI isn't something you can just decide to have. […] It's built up over years, maybe decades, of fostering a culture that embraces risk and learning from failure.

Part 3: Factors Contributing to Expectations of Overall Industry Disruption

Our analysis identified two key factors associated simultaneously with the threat of displacement, GenAI as a driver of competitive advantage, and anticipated sector disruption: the importance of pattern recognition and modularity.

Pattern recognition

Pattern recognition refers to the ability to identify, interpret, and exploit recurring structures or trends in data, processes, or phenomena. In organizational contexts, it encompasses the capacity to discern meaningful relationships, regularities, or sequences that may not be immediately apparent.

Building on insights from earlier stages, pattern recognition emerged as a key variable influencing executives' perceptions of GenAI. To investigate further, we conducted two executive roundtables: one with participants who rated pattern recognition as important to their business success (A1a, n = 23) and another with those who rated it as less important (A1b, n = 13). Executives in A1a consistently expressed greater concern over GenAI's potential to replace human-driven pattern-recognition functions, while those in the low-importance group showed minimal apprehension and even found it hard to imagine which broader organizational roles GenAI could displace:

A1a (pharmaceutical firm): I think the other thing is now with AI is protein folding and CRISPR [DNA modification technology]. […] And the reason DeepMind did it is they just piled piles of data in; it can calculate things at a monumental rate, and it can work out the following. This is critical to the rapid production of drugs […] The question is […], are we actually going to get rid of some of these laborious testing stages in human beings by trusting the AI to be right? […]

The tests that came out last week were basically looking at breast cancer in women and the AI found more cases, early-stage cases of cancer than the human interventions.

A1b (charity research institute): In our sector, in the same way as any other industry, you're always wanting to […] keep up with your competitors. […] AI solutions are everywhere. […] But, yeah, […] we do think it's going to have this big impact, but we're not quite sure yet beyond some sometimes quite basic operational efficiencies […] what the potential for us might be.

Concurrently, A1a participants systematically aligned GenAI capabilities with opportunities for strategic differentiation in pattern-recognition-intensive tasks, while A1b participants predominantly framed GenAI's potential in terms of operational efficiencies:

A1a (education technology firm): Our expertise is in our brain through our experience and knowledge and qualifications. So I think it's really about how do we manipulate GenAI to act as one of our assessment experts or markers, almost like a robotic system that does exactly what our expert does, and to what extent can we then control that robotic system […]."

A1b (logistics & manufacturing): Yeah, so the biggest change that I have seen in this current engagement is they have been asked to reduce 10% of their IT budget. And AI has not been touched. […] How can we transform the AI as such, when you talk about their team and the data scientists and the team that they have built, they are still doing smaller use cases. […] I see this will become an important or probably the most important area for [the] C-suite to invest [in] heavily when you talk about transformation.

A1a participants consistently articulated scenarios of industry transformation driven by GenAI, while A1b participants generally framed industry changes in more incremental terms:

A1b (charity research): I think the third sector in general is more of that approach of tentative and not wanting to be left behind. […] But I also think there are some smaller charities who are maybe more able to take the risk and just try things, whereas, you know, we are taking a very risk-based approach to trying new things because there's so much that's unknown about AI. […] I would say the difficulty for us is we don't have a lot of those use cases that you're talking about.

Our analysis of the B2 roundtable revealed additional insights. A partner at a law firm catering to mid-range clients articulated a vision of complete industry upheaval:

B2 (law firm): We will be thinking of added value, and productivity per person will increase […] And sectors will be differently affected […] In law, you could just have AI negotiating contracts by itself, so you don't need lawyers for it, or going to court, and court being automated eventually […] Possibly, this could be the end of lawyers, eventually, but we don't know where this is going to end.

Modularity

Modularity in organizational design refers to the degree to which a system's components can be separated, recombined, and operated independently (Baldwin and Clark, 2000). This architectural approach enables organizations to adapt more quickly to changes, experiment with new technologies or processes in isolated areas, and potentially reconfigure their structure in response to environmental shifts or strategic imperatives.

Modularity emerged as a key variable influencing executives' perceptions of GenAI. To investigate further, we conducted a single executive roundtable with a mix of respondents who were high on modularity (n = 8) and low on modularity (n = 7). Analysis revealed that organizational modularity is associated simultaneously with perceived threat of displacement, factors enabling competitive advantage by leveraging GenAI, and expectations of industry disruption. These relationships manifested prominently in the high-modularity respondents, while being notably less salient among the low-modularity respondents.

A4 (manufacturing): The more modular our processes become, the easier it is for competitors to replicate what we do. It's just the reality of our business.

A4 (software firm): Our processes are so interconnected that it's hard to see how GenAI could simply slot in and replace any significant part. We're excited about this technology but can't really see a clear use case. Nor can our competitors, from speaking with some of them.

A4 (financial services firm): We have tried to strive for a more modular structure. We're acutely aware that GenAI could potentially replace entire functional units. For instance, our data analytics module could be significantly disrupted by AI capabilities. This modularity makes us more adept, more agile, but also more vulnerable to plain imitation.

High-modularity participants systematically aligned GenAI capabilities with opportunities for strategic differentiation in modular organizational structures. In contrast, lower-modularity participants predominantly framed GenAI's potential in terms of incremental improvements:

A4 (technology firm): Our modular structure allows us to experiment with GenAI in specific units without risking the entire organization. We can quickly identify where it adds the most value and scale those applications across other modules. This ability to rapidly iterate and deploy gives us a significant competitive edge.

A4 (healthcare provider): We're looking at GenAI more as a tool to enhance our existing processes rather than fundamentally change how we operate. Our integrated structure makes it challenging to isolate and experiment with AI in specific areas.

As with pattern recognition, there was a marked difference in perceptions of industry-level disruption between the high- and low-modularity groups, with higher-modularity participants expecting more radical change:

A4 (financial services): In our industry, the modular firms are already racing ahead with GenAI integration. We're seeing new entrants leveraging AI to unbundle traditional financial services, creating highly specialized and efficient modules. Everyone needs to act fast or be left behind.

A4 (energy utility): While we recognize the potential of GenAI, our industry's structure and regulatory environment make rapid, transformative change unlikely. We anticipate more gradual adoption and evolution rather than outright disruption.

Roundtable B2 discussions highlighted how modular structures facilitate rapid adaptation and innovation, particularly in larger organizations:

B2 (professional services): It's almost like operate as a network and allow small parts of the organization to go at speed and to change and deliver new products and new services and get closer to the customers at speed. So, I think companies that are able to do that will be the ones that will take a leadership position […].

While the current section contains condensed versions of certain quotes, Table D1 provides a more comprehensive selection and uncompressed versions of participant statements. These extended quotes offer readers additional insight into the raw data that informed our analysis.

Table D1. Coded constructs and example roundtable quotes

Variable	Full Quote
Regulatory Barriers	"So that's a big thing. Now, industry to industry, things will differ. In [the] financial services sector, yes, we are based on it. We will test everything because we are regulated. And there are a couple of bottlenecks. I think [there are] a couple of big walls in front of us. So, one, of course, is the AI regulation itself. How would FSFCA, who regulates us, see it? They have not defined it yet. We reach out to them every other day and they have no idea. We then reach out to the PRA, because everything is divided in these countries. I think there's not one regulation where we can talk and find things. So, it's not being divided between FCA, PRA, and ICO. God knows who's next. Of course, the big tech companies don't like it because they've been asked now to go [and] basically submit everything so that we can validate. It's just the R17 Institute, you know, let's validate. They're very unhappy. They don't want to extract things and run through it because they want to push it to us." "I used to be a regulator, so I'm still very much in touch with former colleagues there and with Jersey's [UK Channel Islands] government. And both of those bodies are very much trying to encourage the adoption of wider fintech and regtech products in order to help the industry. But obviously, I'd say obviously, I think it's obvious that they cannot give any sort of definitive view to industry to say, use this product, we think it's great. Clearly, it wouldn't be appropriate for an authority to endorse a product like that. But industry doesn't appear to be, or appears to be nervous of taking on any sort of product without that level of endorsement, which they're not going to get." "I think some other consulting firms, [CONSULTANCY], for example, they're just pushing and saying, 'Well, the financial services…' They're trying to sell. [CONSULTANCY] is busy here trying to get more business. Get that reporting. But they are basically saying that advisory by robots. Robo-advisory and stuff like that." "Technically, even humans as brokers, we are not allowed to advise. We can recommend or we can provide information. Even not recommend. The words are very clear. Advise for this. And now, not a human, you ask an avatar who is picking up 20 tons of information from the dark web and giving advice that, 'Hey, you should be buying this and that and that.' And you buy it. And you lose all your money. Who is responsible? This is a huge issue."
Sectoral Conservatism	"The pharmaceutical and life sciences industries are extremely conservative. When I moved from the financial sector to life sciences, it felt like stepping back a century in terms of how things were done. Although there are improvements, the sector remains very sluggish to change." "As people have said, the financial services industry is conservative, and without wishing to perpetuate any sort of stereotypes, we're not complete hicks in the sticks in Jersey, but perhaps we're a little bit more cautious than other people in the big smoke might be. So, there is all of that to contend with as well. This cautious approach is something we have to contend with as well."

	“I think there is, as I said, there is a culture around fear of the new technology and what it means. And perhaps there’s not enough understanding also of the impacts or the implications or the concerns around the bias and the risk aversion that people have around the bias that is there. But I do believe that those who use it, who actually take the risk, have the risk appetite to say, ‘I want to integrate this into my business,’ who have perhaps a more, you may not call it ‘first user advantage,’ but you might have an advantage against your competitors.” “I think that, again, having an advertising campaign that’s a bit off is one kind of risk. But having a bridge that is a bit off, or receiving advice on your health? That is a completely different story altogether. Certain sectors, such as engineering and healthcare, demand a high level of output accuracy due to the significant consequences of errors. In these industries, precision is paramount and even minor mistakes can have serious consequences.” “When it comes to perhaps in the reality of the stats, financial services, for example, is not picking up on it. Financials need precision and AI has a habit of being drastically wrong a lot of the time. That might be accurate if you want something between one and a million. But if you want something that is between 1 and 1.1? No, it’s not good enough.” “Do you think I’m going to buy and invest my money just from studying AI? As I said earlier, I would still go out and look for a person to give me good advice. But it is because I don’t trust it. Not because the AI is better than the humans, maybe the humans are the same, but because it’s a person I trust. I think the cost will be one factor. But how quickly we will start thinking that it’s a title of displacement. But if you generally ask, I think there will be a fear in general for that mundane stuff that we do. As I said, 20 pages, maybe I have to have five people doing all my section screens. There will be fiscal checks, one, two, three, four checks. I’m not going to do that. I am not going to do that.”
Relational Capital	I come from a very knowledge-based, you know, professional service in my life, IT service most of my life. And then, you know, marketing and advertising. Where a lot of your work is very much around, you know, knowledge, data, content. And weaving through lots and lots of data that you have accumulated through years of acquisitions and complexity and all of that. So, all of those dynamics exist. It’s just not a big regulated… I just don’t come from a big regulated financial service industry, right? So, I think in many of those industries, operational efficiency, over time as people are learning, will lead to massive initial transformations because costs will come down significantly and people will be able to use their time on more human-type relationship areas of focus.”
Technical Knowledge	"I think in terms of our industry, [...] it's all about the application of technical knowledge. We're consultant engineers, so it's about how we look at data and how we interpret it. I think the big fear, [...] especially for us as an SME, is that larger companies may be able to leverage GenAI [...] and render us useless. [...] It's how we will use GenAI to provide better information and results that's going to keep us ahead—but if you stay back, I think you're dangerously getting overtaken. [...] This illustrates the question: did we have an edge because of our ability [to interpret data]?" “Technical knowledge, I think, is more like a multi-step, everyone will know, everyone will learn, everyone will read. So, I don’t think that’s going to make any difference anymore.” “If your business still relies on technical knowledge, then you’re toast, basically. We don’t see any benefit, frankly, in trying to hang on to technical knowledge nowadays. It is no longer a differentiator and won’t distinguish your business in any way, shape, or form.” “The hierarchy of firms is going to shift in our industry for sure. Those firms with technical expertise and sophisticated digital infrastructure are going to realize their differentiation has been gone [...]. We’re not going to be completely substituted, we [humans] are still needed to manage statistical chaos [...] Differentiation is going to more likely center around who best manages this chaos.” “On the technical knowledge piece, I think one of, and I think this transcends industry sectors, there’s been more and more contracting out, as it were, to specialist organizations. So, I don’t think any of us probably appreciate what the balance is between in-house versus out-of-house, as it were.”

Proprietary Data	"You know, collaborations between pharma companies on developing a vaccine involve a lot of intellectual property, licenses, and terms. To illustrate the point, imagine two law firms who have completed French nuclear energy projects. They have to navigate planning laws, indemnities, liability allocation, supply chain issues, government funding, and other external funding. But you can't just put that into ChatGPT and get an answer to draft a French nuclear energy contract. It's impossible because the system isn't trained on that specific data, which likely exists only in a few cloud-based files. That data is intellectual property—it's incredibly valuable, high-end, and rare. And we have billions of such valuable data points all over the world." "If I look at the second model of strategy consulting, you know, when I started in Booz Allen in 1995, they had a better knowledge management system then most professional services organizations have now, with the exception of now the other McKinsey, Bain, and BCG. When we compete with McKinsey, Bain and BCG, we know that you guys can pull together a deck of 50, 100 pages on an industry topic in a way that no one else can, in a way that actually we can't because we have… our risk management rules prevent us actually from doing that a lot. So that gives you a competitive advantage that we don't have." "We've been collecting data from thousands of client engagements over decades, but we've barely scratched the surface of what insights we might unlock. With generative AI, we're beginning to see our historical data in a new light. It's not just about what we learned from each project individually anymore. We're excited about the patterns and insights that AI might reveal across our entire body of work. We don't even know what questions to ask yet, but we're certain there's immense value hidden in our data that could revolutionize how we serve our clients." "If I take the world of, you know, financial diligence, which we are probably the world number one in doing, we have done more financial diligence exercises than almost anybody else put together. We know how to do that. We've got the historical data. We've got the metrics and we've got a bench strength of thousands of people who can help effectively train a model to do that."
Data Cleanliness	"Financial services typically will have enough data anyway. It's just a matter of whether the data is clean enough. And that enables you to be able to build a model that understands the different types of data and can be fine-tuned on that data." "We have all this proprietary data that's incredibly valuable, but accessing it is a nightmare. The effort to merge and clean the data is enormous, and we're not even sure if we can do it successfully. It's a major obstacle in utilizing our data to its full potential." "But the data challenge in large non-digital native companies, of course, is huge, either because the data is all over the place, not synchronized, not aligned, and therefore maybe not clean enough to be able to really use for some of the training, the fine-tuning that might be required, but also sometimes not even enough data to be able to really use it for fine-tuning. And some of the things that I'm seeing as I talk to people is the opportunity to actually join forces in industry in a way that you can hold on to your own data, but still put your data through a model that enables you to train that model, but you don't have to expose your own data." "It's more around how you're structured and how you're able to move at speed, more so than in this particular case, the data, because I think some of the data is also, smaller companies are able to access that." "Data itself is a huge issue for our industry. Huge controversies. We still can't have a 360º view of our customers. Data is across thousands and hundreds of systems, especially in the insurance sector. Banking sector is quite similar. In the insurance sector, not one organization has a single policy system or a claim system. We have hundreds of them. It's very complex. So, we don't know what the true value is, or where is the data. And anything wrong with that data is not correct. So, again, big question in terms of that. Third is the issue of operations resilience […] Of course, the DORA Act, the Install Operations Resilience Act, which got enacted in the European Union… So, data is a huge issue. Then how to manage data models and all that stuff—huge issue."

	"The perception of the businesses is, 'My data is my data.' That's a competitive advantage against anything else. And I've done this for the last 20 years and it has not worked. You know, we set up insurance for Embryo. We got all insurance companies to send their Q data or claims data in to process everything. What happens in IB is nothing but running those data in silos. I said it doesn't make any sense. Because if Allianz is having a claim and VWare is having a claim from the same policyholder, you just can't find fraud. And they would never mix the data. Similarly, I was running the Lloyds data center. That's another… They did the information depository management system. We spent billions to upgrade that. It has built [up] 800 years of data. Structured and structured. Okay? Now, the Lloyds marketplace, obviously, it's not one company. There are 300 syndicates, 500 brokers still there. We brought it together when we started providing the services and offering to say, you know, 'You can do this and that.' We literally had to start writing to 5,000 people, every company. 'Can you give me an approval? Can you give me a 99% significance?' We couldn't even run it. And I was sitting with [name] and others and saying, 'What the heck? We spent billions here.' We can't do anything with that system other than just storing data. So, it's very hard." "We're sitting on a goldmine of data, but much of it is protected by client confidentiality rules. It's a Catch-22. We can't bring in outside help to clean and organize our data, which slows us down. But it also protects us from big tech companies swooping in to acquire our data. We have to solve this puzzle internally, which is challenging but could ultimately be key." "So if you take a WPP or you take a Publicis or even Denysu, a lot of them have grown significantly through acquisition and their data is very messy, and there is a lot of investment required to get them onto the same platforms and have the data being interpreted in the same way. So the question becomes, instead of throwing all my costs into trying to fix that infrastructure, does that make sense, or do we stop doing that, leverage it more for efficiency around the products that we develop for our clients, and actually allow the disaggregated, almost small companies, several small companies, as opposed to trying to be one big company that have a competitive advantage of scale."
Tacit Knowledge	"In our sector, tacit knowledge is the intricacies behind building a wall and then plastering it. Expert plasterers know exactly what they're doing, and it's quite difficult to replicate that with a machine, though we can do it with brickwork. There comes a point when perhaps we'll be able to do it with plaster as well… Our expectation is that we have the people with the best understanding of these tacit features and hence will be able to use generative AI better than others." "I can, again, give an example from what we've done and what we've seen. I think if your business is relying on technical knowledge still, then you're toast, basically. I mean, we've just sort of issued a free chatbot that we've developed, which isn't full generative AI, but it's the only example I've got. It's the best example that I've got, which we've trained up on the AML, CFT, CPF regime in Jersey. And this is obviously something that we advise on fairly frequently. We've had colleagues, clients and so on coming to us and saying, well, aren't you putting yourselves out of business? The answer is, well, frankly, no. If you know where to look in the regime, the answers are there already. Our skill is more in what you're calling [the] tacit knowledge side of things. So, the know-how, more of an interpretive skill, the communication side of things." "Take presentation making, for example. It's a skill we have to train our juniors into: what makes a compelling presentation. A lot of this is under the surface. Now, with AI potentially taking over these tasks, we're worried about how our juniors will develop that critical eye, that intuition for what works. It's not just about the end product, it's about the process of learning and developing judgement. We're grappling with how to ensure our future leaders still develop these crucial tacit skills in an AI-augmented environment." I mean, to be honest with you, [...] the challenge is, do we even know exactly what our capacity is? [...] Do we actually have the baseline data in the right format to say [...] how many engineers we have? Basically, the simple question of what it would take to deliver this project in a codifiable manner, which says [...] a person in my team is an engineer of this level, he has skills in this and this and this, and he can do a project of this complexity. I'm afraid we don't

	have that. [...] So, I feel like there's a bit of catch up that is needed to even get to a certain level of base data brilliance to enable this [leveraging of generative AI]. [...] "Let's take the example in a council. When people do, let's say, cash allocation, when a voice comes and payment and the internet, but a lot of things are still done manually. And then comes AI too, which does a lot of this kind of things. When you do implement this kind of things, where do you start? You are asking the accountants of the base, secret tacit knowledge and they ask you, 'Can you share your cheat sheets with us?' Because, you know, there's some things are obvious, rules but there's something where you just, they just know by experience that if this customer is paying this way it's a little bit late and what happens? Based on this kind of tacit knowledge, it can be plugged in, and this is really a part of learning. It's not generative AI, it's alteration AI."
Organizational Flexibility to Experiment	"Yeah, the possible reaping of benefits… China seeds clouds in order to prevent droughts, and America first used cloud seeding. They had one terrible event where they seeded clouds and it possibly intensified a hurricane and killed a lot of people, but China regularly uses that. You need a pretty good forecast, and that's something where AI could help a lot. They seed clouds to prevent droughts in certain areas, whether that's hydrotown areas or crop areas. So, things like that where people are willing to do something slightly outside of the norm to reap the benefits of the forecast. But something says better, can we save the sun? I think it will change the dynamics, but the dynamics are already changing anyway. I think it will accelerate those changing dynamics." "As long as the entire system is stuck with all of these processes and procedures that they implemented years ago, so finally, there is also a big barrier that we cannot properly enter into it because as long as this [new technology] provider doesn't [provide any backward capability], then you're stuck with the [old] system." "The ability to experiment freely with new technologies like AI isn't something you can just decide to have. This has nothing to do with AI, in fact. It's built up over years, maybe decades, of fostering a culture that embraces risk and learning from failure. By the time a disruptive technology like generative AI comes along, it's almost too late to start building that flexibility. It's something that happens over the course of an organization's history."
Pattern Recognition	"I think the other thing is now with AI is protein folding and CRISPR. The thing about protein folding is that even though you know what the atom, what the atomic structure is in a polypeptide, it's still, people don't know why it folds in the way it does. And the reason DeepMind did it is they just piled piles of data in, it can calculate things at a monumental rate, and it can work out the following. This is critical to the rapid production of drugs, absolutely critical to the rapid production of drugs. The question is, are we going to allow, goes back to rhesus monkeys and human beings, are we actually going to get rid of some of these laborious testing stages in human beings by trusting the AI to be right? We're already facing this. The tests that came out last week were basically looking at breast cancer in women and the AI found more cases, early-stage cases of cancer than the human interventions." "Yeah, I think that comes back to the thing of not wanting to miss an opportunity. In our sector, in the same way as any other industry, you're always wanting to keep up with your… in charities, we don't like to think of it like that, but keep up with your competitors. So, if they're doing certain things, then we want to embrace the same opportunities. And, you know, AI solutions are everywhere. So, yeah, I guess that's why, as well, we're just taking the approach of finding what is out there, contributing to different discussions to kind of stay conscious of what's happening. But, yeah, there is a slight element where a bit like some of your survey results so far show that we do think it's going to have this big impact, but we're not quite sure yet beyond some sometimes quite basic operational efficiencies, beyond that, what the potential for us might be." "Because I think we're still in the process of understanding GenAI in terms of it being the knowledge-bearer, if that makes sense. So, I don't know how far we in the education sector are going to be utilizing GenAI as an organism to design products, design content, because we still need experts. Our expertise is in our brain through our experience and knowledge and qualifications. So I think it's really about how do we manipulate GenAI to act as one of our assessment experts or markers—almost like a robotic system that does exactly what our expert

	does. And to what extent can we then control that robotic system so that it doesn't go haywire or manipulate the content in such a way that it causes some level of malpractice?" "The cost reduction is especially [in] the current economic climate, most of the big corporations are affected. And there is another element where this is going into their innovation lab is: how can we look at [a] use-case-driven approach, as you're rightly saying, to create growth. So, growth could be how to optimize market, how do I do sales better using the set of platform and tools and taking a use-case-driven approach. But currently, only based on my personal experience, the cost reduction and growth are the two different use cases that are being looked at. Yeah, so the biggest change that I have seen in this current engagement is they have been asked to reduce 10% of their IT budget. And AI has not been touched. The budget is not just reduced from other areas. The idea is, can we reduce it, but then we move it into this bucket. And this is like a very big challenge for them is about reducing costs, but also keeping ahead of times. How can we transform the AI as such, when you talk about their team and the data scientists and the team that they have built, they are still doing smaller use cases. And they are solving some things which have been patented and they're doing crazy stuff over there. But your question, I see this will become an important or probably the most important area for [the] C-suite to invest [in] heavily when you talk about transformation. That is already happening for them." "I think the third sector in general is more of that approach of tentative and not wanting to be left behind, but not yet doing as much, partly to do with resource, not having as much to put into AI. But yeah, certainly that tension between cautious approach and wanting to try new things and follow the rest of the curve within the sector… It's a good question. I mean, I think 'yes' is the answer, realistically. But I also think there are some smaller charities who are maybe more able to take the risk and just try things, whereas, you know, we are taking a very risk-based approach to trying new things because there's so much that's unknown about AI. And there's so much we want to be careful about—what we do with our support, or data, or research data, or whatever. So we're quite cautious, whereas I do know some smaller charities who are, you know, very small and they're just, 'Oh, we'll just try this'—just kind of trying anything. I would say the difficulty for us is we don't have a lot of those use cases that you're talking about. Like, I'd like to see more discussion within my sector, just within the third sector, about how AI is being used, generative AI, how it is being used effectively. I would say there's some suppliers that are coming to us with solutions where they're saying, 'Oh, this will transform your fundraising capabilities' and whatever, and they offer you that. But I don't know that the reality looks like it would be the case. "We will be thinking of added value, and productivity per person will increase. And we will see things which we used to do, not to do anymore. For example, PowerPoint presentation, which was taking hours and zillions of junior associates, would disappear, just because the machine will be doing all of that now. So, we will need to see a different model to support this, and I think two more things. The one is that there will be a common base for professional services, so there will be a different way to do PowerPoints, or presentations, or videos, or whatever that will be, that will be the way we will be communicating in the future. And sectors will be differently affected, so we don't know how much of this AI will penetrate consulting, or legal services, or other kind of services. It could be more intrusive in other parts, and less intrusive in others. In law, you could just have AI negotiating contracts by itself, so you don't need lawyers for it, or going to court, and court being automated eventually, and not needing to be doing a lot of litigation work for that. Possibly, this could be the end of lawyers, eventually, but we don't know where this is going to end."
Modularity	"The more modular our processes become, the easier it is for competitors to replicate what we do. It's just the reality of our business." "Our processes are so interconnected that it's hard to see how GenAI could simply slot in and replace any significant part. We're excited about this technology but can't really see a clear use case. Nor can our competitors, from speaking with some of them." "We have tried to strive for a more modular structure. We're acutely aware that GenAI could potentially replace entire functional units. For instance, our data analytics module could be significantly disrupted by AI capabilities. This modularity makes us more adept, more agile, but also more vulnerable to plain imitation."

	"Our modular structure allows us to experiment with GenAI in specific units without risking the entire organization. We can quickly identify where it adds the most value and scale those applications across other modules. This ability to rapidly iterate and deploy gives us a significant competitive edge." "We're looking at GenAI more as a tool to enhance our existing processes rather than fundamentally change how we operate. Our integrated structure makes it challenging to isolate and experiment with AI in specific areas." "In our industry, the modular firms are already racing ahead with GenAI integration. We're seeing new entrants leveraging AI to unbundle traditional financial services, creating highly specialized and efficient modules. Everyone needs to act fast or be left behind." "While we recognize the potential of GenAI, our industry's structure and regulatory environment make rapid, transformative change unlikely. We anticipate more gradual adoption and evolution rather than outright disruption." "So I think that sometimes, while these companies may have big treasure troves of data, the size may hinder their ability or hamper their ability to very quickly adjust and change to, as we're seeing, things changing on a daily basis for industries and for clients. So, I think that companies that are able to, even if they're very large, maybe modularize themselves in a way that, while they have a consistent pipe of consistency across the business they have, they're able to allow small parts. It's almost like operate as a network and allow small parts of the organization to go at speed and to change and deliver new products and new services and get closer to the customers at speed. So, I think companies that are able to do that will be the ones that will take a leadership position, not necessarily just the fact that they're incumbents, because I think incumbents could be hampered and held back." "But I think that's precisely where large organizations underestimate the threat of AI. Which is that it is not just cost-cutting in terms of 'I can do this job for less,' but that if you cut costs of doing a job dramatically sometimes, that is much more consequential to the disruptor than the incumbent. In the sense, if you can now do a job much, much cheaper, there's a lot of second-order effects. I can charge now differently. One of the things now that professional services is that we often charge by resource. So, butts per seat or consulting hours, lawyer hours. Now people can charge per task. Are you now going to say to your consultants and your agents that you're now charged per task? There would be a revolt if people's salaries were to be changed in that way. But then an AI disruptor can actually do that and charge per task. And so, the cost-cutting aspect of this doesn't matter all that much to the incumbents, but it actually is the greatest advantage to the disruptor. 'I can do something cheaper; I can completely disrupt the way that you do business.'" "There was talk of us being acquired by a private equity firm many years ago. In response, we made intentional decisions to make our structure less modular to decrease the risk of being picked apart piece by piece—you know, to avoid becoming a body shop." "And I think it might be also again different for different consulting firms, but just talking about the one I know […] We have three layers of what we would call analysts. So, we have the associate that is joining [REDACTED] and that can ultimately become an equity partner. He or she is being supported by a knowledge team. […] And then we have specific research teams that churn [out] company reports and things like this. […] What will be impacted is our knowledge teams and our research teams. But this has been separated, I would say, like 15 years ago where we said, 'Actually, the resource junior associate is so valuable that we don't want him or her to go into company reports, to compile the two pages [on] logistics market 1995 as [REDACTED] did in his first year.' […] Because these are the guys who then need to write the slides. These are the guys who need to do their analysis. These are the people that later will become project leaders. And that's the pyramid you need to have."

References

Akerlof GA. 1970. The Market for 'Lemons': Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics* **84**(3): 488.

Breschi S, Malerba F, Orsenigo L. 2000. Technological Regimes and Schumpeterian Patterns of Innovation. *The Economic Journal* **110**(463): 388–410.

CMA. 2023. *AI Foundation Models Initial Report*. Competition & Markets Authority. Available at: https://assets.publishing.service.gov.uk/media/650449e86771b90014fdab4c/Full_Non-Confidential_Report_PDFA.pdf.

DiMaggio PJ, Powell WW. 1983. The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields. *American Sociological Review* **48**(2): 147.

Jacobides MG, Brusoni S, Candelon F. 2021. The Evolutionary Dynamics of the Artificial Intelligence Ecosystem. *Strategy Science* **6**(4): 412–435.

Kogut B, Zander U. 1992. Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organization Science* **3**(3): 383–397.

Long JS, Freese J. 2006. *Regression Models for Categorical Dependent Variables using Stata, 2nd Edition*. Stata Press books, StataCorp LP. Available at: https://econpapers.repec.org/bookchap/tsjspbook/long2.htm.

McElheran K *et al.* 2024. AI adoption in America: Who, what, and where. *Journal of Economics & Management Strategy* **33**(2): 375–415.

Podolny JM. 1993. A Status-Based Model of Market Competition. *American Journal of Sociology*. University of Chicago Press **98**(4): 829–872.

Podolny JM. 1994. Market Uncertainty and the Social Character of Economic Exchange. *Administrative Science Quarterly* **39**(3): 458.

Polanyi M. 1966. The Logic of Tacit Inference. *Philosophy*. Cambridge University Press **41**(155): 1–18.

Staw BM, Sandelands LE, Dutton JE. 1981. Threat-rigidity effects in organizational behavior: A multilevel analysis. *Administrative Science Quarterly*. The Johnson Graduate School, Cornell University: US **26**(4): 501–524.

Winter SG. 1984. Schumpeterian competition in alternative technological regimes. *Journal of Economic Behavior & Organization*.