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# How Disruptive Will Generative AI Be?

## A Micro-Level Analysis of Evidence and Expectations

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

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

# Contents




**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.



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# 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.

## Abstract

This study examines executives' perceptions 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 potential impact as differing between and within industries and which organizational, technological, and sectoral variables they perceive as most significant. We find that executives evaluate GenAI's potential disruptive impact through its relation to the perceived value proposition of their own business. When this proposition aligns with GenAI-addressable tasks, executives perceive a greater threat of displacement; when orthogonal, they view GenAI as complementary. Sector-level factors such as regulation are perceived to buffer against disruption, while modularity and pattern recognition influence perceptions of both displacement threat and differentiation potential.

## Managerial Summary

How disruptive will GenAI be? We find that shifting the focus from modular tasks (where GenAI shines) to sectors and business models suggests greater caution and qualification. We draw on qualitative and quantitative analysis of UK directors' assessment and expectations of GenAI's disruptive potential, which vary across and within industries. While executives acknowledge that GenAI could automate tasks and occupations, many believe their organizations' core value propositions remain insulated. Differences in perceived displacement can be traced to whether executives view their advantage as anchored in task bundles or in broader, orthogonal roles, implying that business models matter. Sector-level buffers such as regulation are also seen as shields against displacement. Taken together, our results suggest that GenAI's industry impact may be mediated by positional differences.

**Keywords:** artificial intelligence, generative ai, strategic decision-making, competitive advantage, technological disruption, pattern recognition, modularity

# 1. Introduction

Artificial intelligence (AI)—and, more recently, generative AI (GenAI)—already rivals or surpasses human performance across myriad tasks. Traditional (i.e., non-generative) AI systems that excel at pattern recognition, classification, and prediction with structured data have mastered strategic games (Risi and Preuss, 2020) and out-performed experts in forecasting (Agrawal, Gans, and Goldfarb, 2018; Cowgill and Tucker, 2020). GenAI, built on large language models capable of creating novel content from natural language prompts, stretches further into creative writing (Doshi and Hauser, 2023; Noy and Zhang, 2023) and scientific discovery (Boiko, MacKnight, and Gomes, 2023; Ludwig and Mullainathan, 2023; Manning, Zhu, and Horton, 2024). Firm adoption of traditional AI is accelerating (Bonney *et al.*, 2024) and nearly one-quarter of employees now deploy GenAI weekly (Bick, Blandin, and Deming, 2024). The central question for scholars, therefore, is whether, and how, these proven task capabilities will reshape competitive advantage, organizational boundaries, and ultimately industry structure (Achiam *et al.*, 2024; Bonney *et al.*, 2024; Bubeck *et al.*, 2023; Candelon, Martinez, and Cavin, 2025; Girotra *et al.*, 2023).

Most empirical work to date remains task-based: researchers decompose jobs into tasks, assess GenAI's competence on each one, and recombine those assessments into occupation- and sector-level exposure scores (Brynjolfsson and Mitchell, 2017; Eloundou *et al.*, 2024; Felten, Raj, and Seamans, 2021; Handa *et al.*, 2025; Svanberg *et al.*, 2024). These studies do not claim that exposure alone predicts broader trends; rather, they illuminate possible labor substitution and displacement at the occupation level (Autor and Thompson, 2025). Complementary field experiments show large productivity gains from GenAI in narrowly circumscribed tasks such as customer-support chats (Brynjolfsson, Li, and Raymond, 2025), consulting problem-solving (Dell'Acqua *et al.*, 2023), idea generation (Boussioux *et al.*, 2024), and software development (Gambacorta *et al.*, 2024; Hoffmann *et al.*, 2025; Peng *et al.*, 2023). Together, this evidence clarifies where GenAI might lower cost or raise quality, yet leaves open the question of *whether and when the degree of task-level overlap actually maps onto shifts in competitive advantage, organizational positioning, and industry leadership.* This disconnect reflects a familiar paradox: while scholars project substantial productivity gains from GenAI (Brynjolfsson *et al.*, 2025; Mollick, 2024), empirical evidence of organizational and industry-level impacts remains limited and pessimistic (Economist, 2024, 2025; Mortensen, 2025), underscoring the need to examine mediating mechanisms between GenAI's technological capability and competitive outcomes.

History cautions against a one-to-one mapping from technical capability to industry upheaval. Firms are not mere bundles of tasks; they are socio-technical systems whose boundaries, routines, and resources are shaped by managerial judgment. General-purpose technologies typically yield competitive advantage only after complementary investments in data, human capital, and organizational redesign (Agrawal, Gans, and Goldfarb, 2021; Baldwin, 2024; Bresnahan and Trajtenberg, 1995; David, 1990). Diffusion lags, and heterogeneous returns are the norm (Brynjolfsson and Hitt, 2000; Rosenberg, 1998); prior digital waves show that technology can widen—not compress—performance gaps among firms (Brynjolfsson, Rock, and Syverson, 2017; Iansiti and Lakhani, 2020; Jacobides, Brusoni, and Candelon, 2021; McElheran *et al.*, 2024). Resolving whether GenAI will disrupt or entrench organizational positions, and the role of managerial action, is therefore a critical agenda for strategy research,

given the scale of current investment and the intensity of public discourse surrounding the technology.

To confront this agenda, we build on a rich stream of scholarship showing that technological impact is filtered through executives' cognitive frames (Eggers and Kaplan, 2009; Eggers and Park, 2018; Henderson and Clark, 1990; Tripsas and Gavetti, 2000). A central proposition of this literature is that executive perceptions of new technologies guide resource allocation and strategic direction, and as such, provide a mediating lens to understanding organizational, and consequently, sectoral change (Anderson and Tushman, 1990; Benner and Tushman, 2002; Kaplan and Tripsas, 2008; Tripsas, 1997). Accordingly, understanding GenAI's consequences for competitive advantage and sectoral dynamics requires examining how executives perceive the technology.

This study drew on a unique 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 view these board members' perceptions as particularly critical, since board-level perceptions will determine corporate direction, investments, and firm approaches to technology deployment. Our mixed-methods study followed an abductive, three-stage design (Mitchell *et al.*, 2022; Timmermans and Tavory, 2012) grounded in peer-group protocols (Flick, 1998). Exploratory roundtables surfaced key constructs (Furnari *et al.*, 2021); a follow-up survey quantified relationships among those constructs; and nine targeted roundtables tested those relationships by exposing matched peer groups to identical stimuli (Mitchell *et al.*, 2022)—an approach well suited to a technology that still lacks a dominant design or "killer" use case (Abernathy and Clark, 1985; Anderson and Tushman, 1990).

We find that task–technology overlap is a poor predictor of directors' expectations, which diverge markedly even when executives agree that GenAI can perform many of their firms' tasks. Our central finding is that this divergence is explained by how directors map GenAI onto their firms' core value propositions: organizational displacement is anticipated when the perceived value proposition rests on tasks that GenAI can replicate, whereas augmentation is anticipated when value is seen as orthogonal to those tasks. Many directors therefore acknowledge substantial task-level alignment yet still regard their distinctive organizational value as beyond GenAI's reach. In regulated industries, for example, directors frame value propositions around functions such as the provision of legal liability, assurance, or stakeholder accountability, which GenAI is not perceived to affect. Sectoral regulation thus reinforces these frames by institutionalizing such roles. Because value-proposition frames direct attention to different complementary assets and bottlenecks, firms—even within the same sector—pursue divergent investment paths in response to GenAI.

We assessed the durability and external validity of these findings through three extensions. First, a re-survey and 12 follow-up interviews in July 2025 validated that perceptions remained broadly stable, despite subsequent advances in GenAI capability. Second, following Guzman and Li's (2023) approach to measuring strategic differentiation, we observed that directors claiming immunity had more distinctive value propositions than those anticipating displacement. Third, an out-of-sample roundtable in June 2025 with 27 director-level executives in knowledge-work industries yielded patterns consistent with our results, underscoring their generalizability.

Our findings shed light on the nature of GenAI's expected impact, and more broadly help us rethink the nature of technological disruption. By centering managerial interpretations rather than task inventories, we provide mid-range theory to begin unpacking how GenAI may affect competitive advantage and sector dynamics. A key insight is that executives evaluate disruption through the lens of their business's core value proposition and how they mentally modularize their businesses. When a firm's value proposition is understood as a loosely coupled set of tasks, executives are more likely to anticipate displacement. In contrast, when value is framed as emerging from integrated or orthogonal functions, GenAI is seen as less substitutive to the firm. Sectoral regulation reinforces the latter view by embedding firms in orthogonal value propositions that emphasize assurance and accountability. These interpretations, in turn, shape whether task-level capabilities are perceived to threaten firm- or sector-level positions.

By examining how directors perceive GenAI's relationship to their value propositions, we contribute a more nuanced framework for anticipating disruption. These findings bridge the gap between assessments of GenAI's task-level capabilities and executive perceptions of firm-level disruption, helping explain how and why similar exposure to GenAI can produce divergent organizational views. The findings caution against interpreting task-based exposure as a direct forecast of industry upheaval (Mollick, 2024) and provide a roadmap for future work linking technological capability, managerial cognition, and competitive dynamics.

Thus, this study makes four core contributions to strategy and technological adaptation. First, it introduces the firm's value proposition as a cognitive lens through which executives assess the disruptive potential of GenAI. Second, it bridges task-based AI exposure models with firm-level strategic response, offering a mid-range theoretical explanation for how and when task overlap relates to perceptions of organizational displacement. Third, it advances theory on the *perceptions* of modularity (Baldwin, 2024; MacDuffie, 2013), showing how executives' mental models of their firm's architecture—not technical modularity alone—shape whether GenAI is perceived as substitutive or complementary. Fourth, it identifies sectoral buffers—such as regulation and liability structures—as perceptual filters that mediate disruption expectations across industries.

## 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[1]. Since the public release of ChatGPT in November 2022, GenAI has become the

1 It is important to address the distinction between GenAI and traditional forms of AI when considering organizational and industry impact, as GenAI's unique capacity to expand rather than simply replace human capabilities may represent a different technological paradigm that warrants examination of existing theories of technological disruption. While GenAI can automate tasks similarly to prior predictive systems—such as processing customer inquiries or analyzing data—it additionally enables workers to generate novel content and solve problems beyond their normal capabilities, whereas traditional AI primarily optimizes predefined workflows. Recent experimental evidence demonstrates that GenAI acts as

fastest-growing innovation in history, with some projections suggesting it could drive a $7 trillion increase in global GDP, raise productivity growth by 1.5% over 10 years (Goldman Sachs, 2023), or uplift profit by $4.4tn (McKinsey & Co, 2023). Other observers are more circumspect, however, 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. Nonetheless, by recent estimates, the workplace adoption of GenAI has been as fast as that of personal computers during the 1980s, while overall user adoption has outpaced any technology in history (Bick *et al.*, 2024).

Recent research shows substantial productivity gains when GenAI, in particular, is deployed for discrete organizational tasks. Sizeable treatment effects have been observed across a range of contexts, including customer support (Brynjolfsson *et al.*, 2025), telemarketing (Jia *et al.*, 2024), business-case solving in strategy consulting (Dell'Acqua *et al.*, 2023), idea generation (Dell'Acqua *et al.*, 2024), crowdsourcing (Boussioux *et al.*, 2024), and software development (Gambacorta *et al.*, 2024; Handa *et al.*, 2025; Hoffmann *et al.*, 2025; Peng *et al.*, 2023). These studies consistently demonstrate that GenAI can augment human capabilities in specific organizational tasks, improving productivity.

Extending this task-based paradigm, researchers have continued to map GenAI's capabilities onto tasks and occupations. The predominant approach, consistent with the task-based view of technological change (Autor, Levy, and Murnane, 2003), is to disaggregate occupations into tasks, assess GenAI's competence for each, and re-aggregate the results into occupation- and sector-level exposure scores (Brynjolfsson, Mitchell, and Rock, 2018; Eloundou *et al.*, 2024; Felten *et al.*, 2021; Handa *et al.*, 2025; Svanberg *et al.*, 2024). This method has produced estimates of occupational-level exposures to GenAI, generally placing knowledge-work occupations high on exposure scales and jobs in physical sectors such as manufacturing further down (Eloundou *et al.*, 2024). Crucially, however, the authors emphasize that such scores are intended as inputs to broader analysis rather than direct forecasts of which firms or industries will be upended.

While these exposure scores usefully flag where task substitution is technologically feasible (Acemoglu, 2024; Bick *et al.*, 2024; Svanberg *et al.*, 2024), they do not reveal whether or how competitive advantage, firm performance, or industry leadership will be reconfigured (Candelon *et al.*, 2025). Indeed, historical precedent suggests that the relationship between task-level technological capabilities and industry-level disruption is rarely straightforward. The organizational literature has long emphasized that firms are not simply bundles of tasks but rather complex adaptive systems in which technological change interacts with social structures, established routines, and decision-making processes (Nelson and Winter, 1982).

The history of general-purpose technologies (GPTs) provides compelling evidence for this complexity. For example, integrating computers into business operations required decades of

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an "exoskeleton" enhancing workers' capabilities, equalizing treated workers in tasks (Sack *et al.*, 2024; Wiles *et al.*, 2024). This capability-expanding property distinguishes GenAI's potential as an equalizer from traditional automation, potentially representing a departure from prior technological paradigms, making it theoretically unclear what the organizational and industry-level implications of this technology will be.

complementary innovations in software, networking, and interface design before yielding substantial productivity gains (David, 1990). This “productivity paradox” demonstrates that even technologies with clear task-level superiority may not immediately disrupt industry structures or competitive dynamics (Brynjolfsson and Hitt, 2000; Brynjolfsson *et al.*, 2017).

The effective integration of GPTs typically requires substantial complementary investments in related technologies, human capital, and organizational redesign (Agrawal *et al.*, 2021; Baldwin, 2024; Bresnahan and Trajtenberg, 1995). These investments are not uniform, but shaped by pre-existing capabilities, complementary assets, and strategic positioning (Teece, 1986, 2018). Established theories of technological change emphasize the interplay between technology and specialized complementary assets (Teece, 1986), with incumbents maintaining advantage through such assets even against competency-destroying innovations (Helfat, 2002; Mitchell, 1989; Tripsas, 1997; Tushman and Anderson, 1986)—though misaligned assets can become rigidities (Benner, 2007, 2010; Cohen and Levinthal, 1989, 1990; Henderson and Clark, 1990; Tripsas, 1997). These frameworks, however, offer limited guidance for GenAI, which simultaneously exhibits competency-enhancing and competency-destroying features within the same context (Brynjolfsson and McAfee, 2014; Krakowski, Luger, and Raisch, 2023; Raisch and Krakowski, 2021), rendering traditional predictions of competitive impact limiting (McAfee, 2024).

Yet, technology‘s impact on industry structure remains mediated through executive perceptions (Eggers and Kaplan, 2009; Kaplan and Tripsas, 2008; Tripsas and Gavetti, 2000). While no universal theory predicts technological outcomes, managerial cognition—how executives interpret technologies relative to their capabilities and strategic position—consistently emerges as the unifying factor (Eggers and Park, 2018). These cognitive frames direct complementary asset investments and organizational redesigns, ultimately shaping incumbent success or failure (Benner and Tushman, 2002; Henderson and Clark, 1990; Tripsas, 1997).

Indeed, decades of research detail how mismatches between established cognitive frames and emerging technological logics can derail even technically capable incumbents. Tripsas and Gavetti’s (2000) study of Polaroid shows that top managers’ belief that the firm’s edge lay in instant-print chemistry channeled search toward ever-better film emulsions even as R&D produced working digital prototypes; it was the cognitive frame, rather than the lab, that dictated investment priorities and delayed business-model reinvention. Similarly, Eggers and Kaplan (2009) show that telecoms CEOs who attended to fiber optics early on entered sooner and deployed capital more aggressively, whereas peers fixated on legacy voice lines postponed entry despite having comparable resources. Together, these studies anchor the claim that managerial cognition acts as a dynamic managerial capability that selects which organizational resources are mobilized (and which remain dormant) when a discontinuity unfolds.

Similarly, divergent attentional focus among senior teams compounds into strategic bifurcation within industries (Ocasio, 2011). Kaplan (2008) documents that U.S. newspaper publishers who framed the web as a complementary distribution channel invested early in digital content systems and captured online readership, whereas peers who saw it as cannibalistic doubled down on print efficiency and ultimately lost share. Raisch and Krakowski (2021) more specifically theorize that executives who construe AI as *augmentation* may channel spending toward re-skilling and complementary assets, while those who construe it as *automation* may

prioritize short-term cost cuts—differences that may predict whether post-adoption performance gaps widen or narrow.

This research demonstrates that perceptual divergence, rather than resource endowment per se, drives divergent adaptation paths—making executive perceptions paramount for understanding GenAI's organizational and industry-level impact. Despite extensive theoretical frameworks on technological change and growing evidence of GenAI's task-level capabilities, we lack empirical insights into how executives perceive GenAI's relationship to their competitive positioning and industry structure. While considerable attention has focused on which tasks might be automated or enhanced (Eloundou *et al.*, 2024), we have insufficient understanding of the mechanisms through which task-level capabilities might translate into broader competitive outcomes. This critical gap in our understanding is what we aim to address in this study.

# 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). Understanding GenAI's impact on organizational competitive advantage and sectoral dynamics represents a central question facing industry, academics, and policymakers alike. Thus, an abductive approach is particularly well suited to our research context because, as Choudhury, Moeen, and Wormald (2025) advocate, abduction comes into play when the context presents "a state of doubt or curiosity."

Abduction frequently incorporates purposeful sampling and mixed methods, facilitating a triangulation approach (Jick, 1979) to reveal subtle anomalies (Katz, 2002). The empirical context should be informed by 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 in the data (Bamberger, 2018).

## 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 selected on conceptual grounds rather than for representativeness (Miles and Huberman, 1994). The IoD's composition encompasses significant representation from professional services alongside executives from diverse sectors and firms from startups to

large institutional players. This diversity facilitated the examination of granular differences within sectors, such as comparing regulated and non-regulated professional services, while providing the necessary variance to identify central concepts and underlying mechanisms.

The IoD constitutes a relevant empirical context because it focuses on senior executives whose perceptions carry particular significance: directors determine resource allocation and technology engagement decisions that shape their firms' strategic direction. Given extensive scholarly debate over GenAI's potential impact in knowledge-intensive sectors, the IoD's substantial representation of these sectors offers a targeted sample that is closely aligned with GenAI's specific challenges and opportunities (Bick *et al.*, 2024; Eloundou *et al.*, 2024). The sample provides relevant variance in sectoral and organizational characteristics while controlling for executive seniority and geographic location, thereby enabling insulation from external factors. Focusing on a specific temporal period and executives from a stable membership base further minimizes potential contamination from exogenous technological adaptations (Creswell and Plano Clark, 2018).

While our sample provides distinctive insights, we acknowledge potential self-selection bias (Heckman, 1979), likely capturing executives who are more engaged with 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, 1962). Notably, it is precisely because of this self-selection that our observation of heterogeneity in experiences and expectations regarding the technology becomes especially revealing. Nonetheless, some of our post-hoc analyses serve to address concerns regarding sample representativeness, external validity, and consistency of findings over time. Details are provided later in the manuscript and appendix.

## 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 and how firms in different settings are affected distinctly by GenAI. 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 (Flick, 1998). 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. Based on these, we identified three initial patterns: (1) consensus on GenAI's task-level capabilities across sectors; (2) significant intra-sectoral variance in how executives viewed GenAI's impact; and (3) cross-sectoral differences related to regulation.

These findings suggested that intra-sectoral variation in GenAI experiences and expectations seemed to stem from differences in how executives defined their business value-add rather than contrasting evaluations of GenAI's capabilities. Thus, we refined our research question to explore the mechanisms underlying this heterogeneity. In Stage 2, we asked: *What organizational and sectoral factors explain variance in directors' expectations of GenAI's impact*

*on competitive positioning?* To address this question, we conducted a structured survey with 217 executives from mid-February to March 2024. The survey confirmed significant intra-sectoral variation in displacement expectations, even among executives acknowledging similar degrees of task-technology overlap within their organizations. This pattern suggested that factors beyond task-level competence were mediating directors' interpretations of GenAI's implications for their firms.

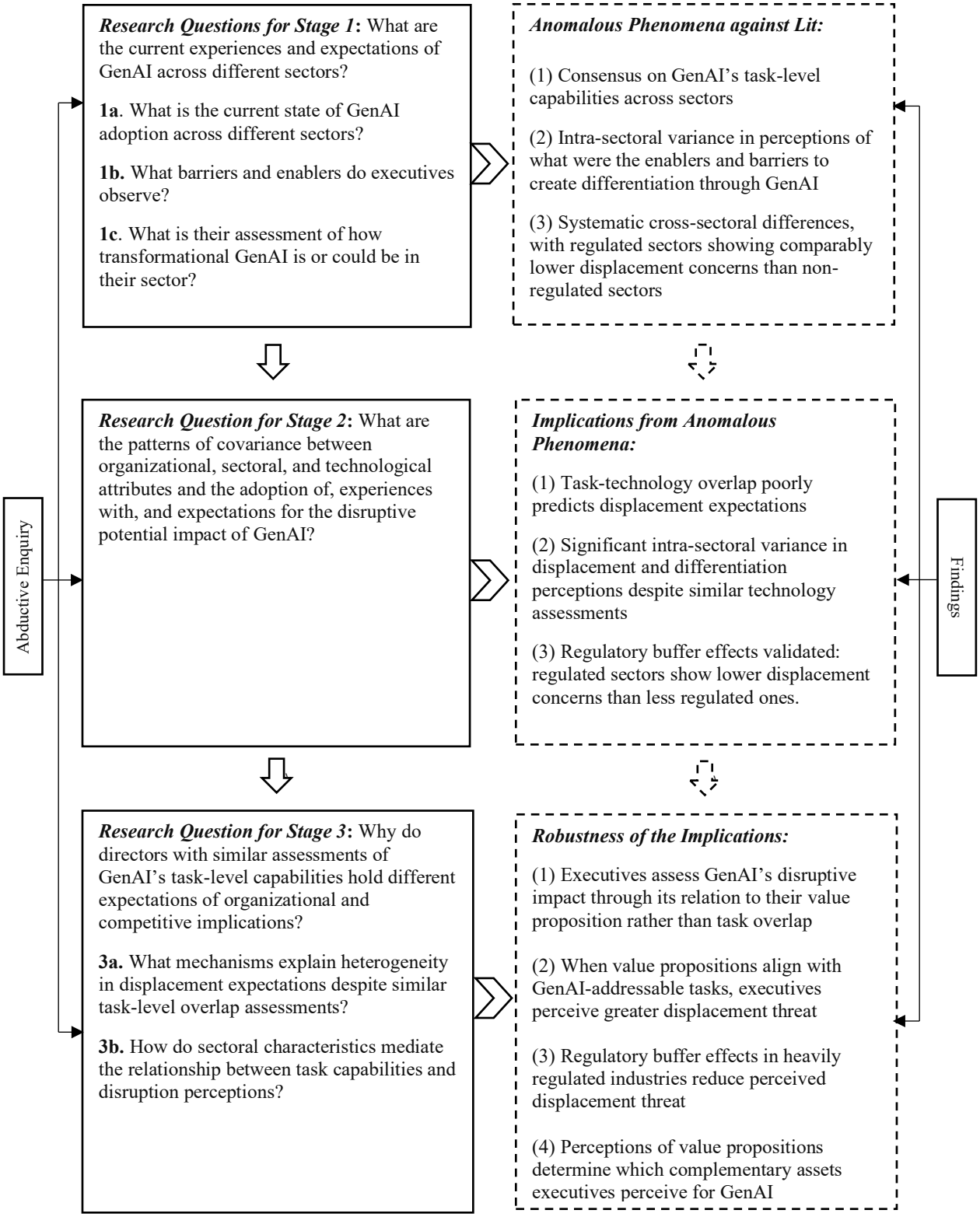
The quantitative patterns from Stage 2 enabled us to partition survey respondents into theoretically meaningful groups based on their displacement expectations and task-overlap assessments. Based on these, we designed Stage 3 to isolate the causal mechanisms explaining why directors with similar assessments of GenAI's task-level capabilities often held markedly different expectations about organizational impact. We conducted nine structured roundtables from late March to May 2024, comprising 163 executives strategically selected to create matched comparisons: seven roundtables comprised survey respondents from similar sectors and firm sizes who had provided comparable assessments of GenAI's task-level competence but divergent expectations of displacement threat, while two additional roundtables included external executives to test generalizability. Each roundtable exposed matched peer groups to identical GenAI scenarios and prompts, enabling systematic comparison of their interpretive frameworks to probe: *Why do directors with similar views of GenAI's task-level capabilities hold such different expectations about its organizational and competitive implications?* Our analysis revealed that directors evaluate GenAI's disruptive potential by assessing its relationship to their firms' core value propositions, rather than through task inventories alone. Directors anticipating displacement consistently described value propositions that aligned with GenAI-addressable capabilities, while those expecting augmentation articulated value propositions they viewed as orthogonal to GenAI's current reach, explaining the persistent heterogeneity observed across both Stages 1 and 2.

To assess the durability and external validity of these findings, we conducted additional analysis from April to July 2025 comprising three elements. First, we re-administered the original Stage 2 survey to 277 IoD respondents in June 2025, engineering the survey instrument with pre-testing to specifically examine whether our core findings remained stable, since GenAI capabilities had evolved, and public discourse advanced, over the intervening year. When we matched the responses to those from Stage 3, we observed high stability and consistency, suggesting that what we captured reflects steady-state perceptual frameworks and is less susceptible to the potential peer-group influences inherent in roundtable settings. Second, we developed an objective measure of strategic differentiation by retrieving firms' website snapshots from the Internet Archive's Wayback Machine, embedding them using doc2vec models, and calculating strategic differentiation scores (SDS) following Guzman and Li's (2023) procedure, triangulating with LinkedIn business descriptions for qualitative validation. We found that executives' self-reported value proposition distinctiveness aligned consistently with higher strategic differentiation scores, suggesting that directors' assessments correspond to their organizations' observable online positioning (although this does not allow us to establish whether executive and organizational self-descriptions align with what customers actually value). Third, we conducted an additional peer-group roundtable in June 2025 with out-of-sample respondents primarily from knowledge-work industries, maintaining a similar descriptive composition to our Stage 3 samples, to examine whether our results resonated

more broadly; we found general consistency with our core patterns. Detailed analysis of our validation is provided in the appendix.

Our mixed-methods approach, while comprehensive, has inherent limitations. Roundtable discussions may introduce social desirability biases (Nederhof, 1985), potentially influencing executive responses. Despite potential pressures for conformity, however, 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; Arthur, 1989; Eggers, 2014). The persistence of varied industry perceptions, even in settings that might induce convergence, and vivid discussion with differing views, is promising (Flick, 1998).

## Figure 1: Progression of the abductive analysis



# 4. Stage 1: Observations from Initial Roundtables

## 4.1 Methodology

As Timmermans and Tavory (2012) 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?*

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 online 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 Consensus on Task-Level Capabilities of GenAI

A key rationale behind our design choice of open-ended roundtables was to observe where executives agreed or disagreed with each other (Flick, 1998). Across the five roundtables, which were structured around knowledge-work verticals that rank high on occupational exposure scales (Eloundou *et al.*, 2024), participants demonstrated strong consensus regarding the overlap between GenAI's capabilities and many of their everyday tasks. When asked about their experiences, executives rarely disagreed on whether GenAI's capabilities overlapped with cited tasks. Most of these assessments were based on their own experiences with using ChatGPT and Claude, although some were based on their own bespoke models.

Executives consistently identified similar task-level capabilities, frequently mentioning writing emails, producing summaries of company calls, translating documents, proofreading, brainstorming, writing job descriptions, and generating initial drafts of content. This consensus extended to more sector-specific tasks as well. Legal executives uniformly acknowledged GenAI's effectiveness in contract review and legal research. Management consultants commonly cited its capacity for assisting in idea generation and brainstorming. Financial services executives agreed on its utility for report generation and content synthesis. Media and communications executives concurred on its capabilities in emulating visual and writing style given the right input.

## 4.3 Why Does Heterogeneity Arise in GenAI Experiences within Sectors?

We began to observe heterogeneity in responses when prompting participants to discuss their experiences and expectations regarding GenAI's impact on their competitive differentiation. These divergences appeared to stem not from varying evaluations of GenAI's capabilities, but

rather from different perspectives on what resources needed to be bundled, and consequently which barriers had to be overcome, in order to achieve differentiation.

Executives identified divergent sources of competitive advantage from GenAI. We categorized these resources as enablers; they are summarized in the left-hand column of **Table 1**. Within the same sectors, some emphasized human capital advantages (e.g., superior prompting skills, technical expertise for deployment), while others focused on proprietary assets (e.g., document libraries, historical client data) or relational capital and trust. This divergence was particularly evident among advertising executives: one argued that "the people with the technical knowledge still are needed to use GenAI to generate differentiation," while another countered that "GenAI is based on the uniqueness and depth of your data, which [our firm] has mountains of." While executives broadly agreed on GenAI's task-level capabilities, they disagreed on what organizational resources the technology would need to be bundled with to create competitive advantage in their respective industries.

Executives also identified organizational impediments to leveraging GenAI. We categorized these factors as barriers; they are summarized in the right-hand column of **Table 1**. Several executives in non-regulated professional services cited organizational complexity and the degree to which their business processes were modularized as challenges. A consulting executive noted: "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." Others pointed to integration difficulties with existing technology stacks, leadership resistance ("CEOs are at the position they are at because what they have done has worked for the past decade"), and talent constraints ("We just don't really have the right people within our organization to lead its implementation").

Through evaluating these responses, it became evident that heterogeneity within sectors reflected executives' different conceptualizations of their firms' value propositions. For example, two management consulting executives identified different enablers based on their core business value-add: one whose firm delivered value through data analysis prioritized proprietary data access, while another emphasizing client relationship management focused on tacit knowledge and relational capital. Thus, while executives agreed on GenAI's task-level capabilities, they diverged on how those capabilities would affect their specific value propositions, leading to different assessments of relevant enablers and barriers.

## 4.4 Why Does Heterogeneity Arise in GenAI Experiences across Sectors?

When comparing the average consensus between the five roundtables, we also observed systematic differences in how executives from different sectors perceived the potential for GenAI to disrupt their core businesses. While executives across all sectors recognized similar task-level capabilities of GenAI, their assessment of whether these capabilities would disrupt their fundamental value proposition varied considerably between sectors.

Executives in regulated professional services such as law and financial services consistently expressed confidence that GenAI would primarily complement rather than displace their core offerings. They characterized significant industry disruption as "unlikely in the foreseeable future," focusing instead on localized productivity gains and operational efficiencies. 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 maintained that human elements would preserve their value proposition: "I buy consulting services because I trust the team that is going to deliver. So, trust is key [...] a consulting project is not just advisory [...] but it's mainly implementing change in your company. [...] And change management is done by people at the end."

This heterogeneity led us to identify sector-level factors that appeared to mediate executives’ displacement concerns. Three key “buffers” emerged: (1) legal liability and certification requirements, particularly in regulated professional services where clients “can’t sue the AI if it gives them wrong advice”; (2) output accuracy demands in sectors such as insurance, where “a miscalculation could be catastrophic”; and (3) institutionalized behavioral conservatism, especially in financial services, where executives acknowledged that firms were “notoriously slow” with technology adoption. These sector-specific characteristics functioned as perceptual filters, with executives in sectors possessing stronger buffers (e.g., law, financial services) exhibiting less concern about disruption than those in sectors with weaker institutional protections, despite comparable assessments of GenAI’s task-level capabilities.

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

| Enablers | Barriers |
|---|---|
| *Proprietary data being supercharged through GenAI*<br>• "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)<br>• "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)<br><br>*Tacit knowledge in human labor complementing GenAI's lack of judgement*<br>• "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)<br>• "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)<br><br>*Technical expertise in humans correcting and verifying GenAI's output inaccuracy*<br>• "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)<br><br>*Relational capital and client trust buffering the firm against selection issues*<br>• "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)<br><br>*Organizational risk appetite enabling adoption and first-mover advantage*<br>• "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 […], 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*<br>• "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)<br>• "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)<br>• "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)<br><br>*Organizational leadership being uninterested or not understanding the technology*<br>• "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)<br>• "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)<br><br>*Inability to identify and/or attract the right talent to deploy the technology*<br>• "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)<br>• "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)<br>• "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) |

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

# 5. Stage 2: Structured Survey and Analyses

## 5.1 Methodology

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?* Building on Stage 1 insights and established constructs, we fielded a concise Qualtrics instrument to the entire UK Institute of Directors in February–March 2024. Five-point Likert items captured perceived GenAI enablers/barriers, functional adoption, expected impact, and controls for firm size and executive technology attitudes; to enhance the validity of self-reported data, respondents were promised a personalized benchmark comparing their firm with peers. The survey yielded 217 complete responses (10.9% response rate), all from director-level or higher executives across diverse sectors. Randomized item order, centered scale anchors, and other design safeguards minimize common-method bias, providing a robust cross-sectional snapshot.

## 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 online appendix. In all, Stage 2 analysis corroborates many of the propositions from Stage 1, while revealing anomalies that merit further examination.

Firstly, we observe sizeable intra-sectoral variance regarding the importance of certain features. Within professional services, for example, 24% of executives reported that pattern recognition was not at all or only slightly important to their business success, with 17% reporting it as mildly important and 58% reporting it as very or extremely important. Similar spaced-out distributions were observed for relational capital, market insight, technical knowledge, and certification of final output. All in all, this corroborates our observation from Stage 1 that executives position their business value-add differently within sectors, seemingly reflecting different "moats."

Secondly, we find evidence supporting the Stage 1 observation that executives who perceive the regulation of their sector as higher exhibit comparatively lower concerns for displacement. We find that these results also hold within broader sector groupings: for example, legal, financial services, and accounting firms show markedly lower perceptions of displacement threat than those in management consulting and technology consulting.

Thirdly, we observe divergent perceptions regarding expectations for GenAI's potential to unlock new forms of distinctiveness and 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." Our ordinal logistic regression (OLR) results, which we detail in the online appendix, corroborate these propositions.

All in all, these findings support the empirical validity of our Stage 1 observations while revealing several anomalies that merit deeper investigation. Notably, the relationship between task-level overlap and perceptions of displacement threat appears to vary systematically across sectors. While executives in less regulated sectors consulting show stronger associations between task-level capabilities and displacement concerns, this relationship appears to weaken or dissipate entirely in more regulated sectors. This pattern suggests that factors beyond pure task-technology overlap are mediating executives' interpretations of GenAI's disruptive potential. Our findings also suggest that separate sets of factors influence executive perceptions of GenAI's potential to increase distinctiveness versus its threat of displacement, indicating these are not simply inverse phenomena but operate through distinct mechanisms. Thus, we ask: *Why do executives with similar assessments of GenAI's task-level capabilities hold such divergent expectations about its organizational and competitive implications, and what mechanisms explain the apparent sectoral differences in how task-level overlap translates into displacement concerns?*

# 6. Stage 3: Insights from Follow-Up Roundtables

## 6.1 Data Collection, Coding, and Sensemaking

To address the questions emerging from Stages 1 and 2, we conducted nine executive roundtables with 163 director-level executives. Seven paired roundtables (Part A) were strategically composed based on executives' Stage 2 survey responses, creating matched comparisons along key dimensions: pattern-recognition importance (high/low), proprietary data importance (high/low), strategic uncertainty (high/low), and modularity (mixed). Two additional roundtables (Part B) tested external validity with non-IoD members, with 21 participants engaged in strategy and policy from the IoD in B1 and 30 executives primarily from private equity firms in B2, designed to provide an "outside-in" perspective to our sensemaking.

Part A roundtables lasted 2.5 hours each, while Part B sessions were extended to 4.5 hours. All followed a semi-structured format with an inside-out approach, examining three key questions:

(1) *What factors drive perceived displacement threat?* (2) *What enables leveraging GenAI for competitive advantage?* (3) *What shapes industry disruption expectations?* All sessions were recorded and transcribed.

We analyzed the data through systematic comparison of paired roundtables to identify divergent interpretations of identical stimuli, cross-variable analysis to uncover interactions, and insights from executives who had transitioned between sectors. Following established qualitative methodologies (Charmaz, 2006; Gioia, Corley, and Hamilton, 2013), we employed iterative coding from first-order concepts to aggregate theoretical dimensions. Detailed methodological procedures, participant demographics, and coding structures are provided in the online appendix.

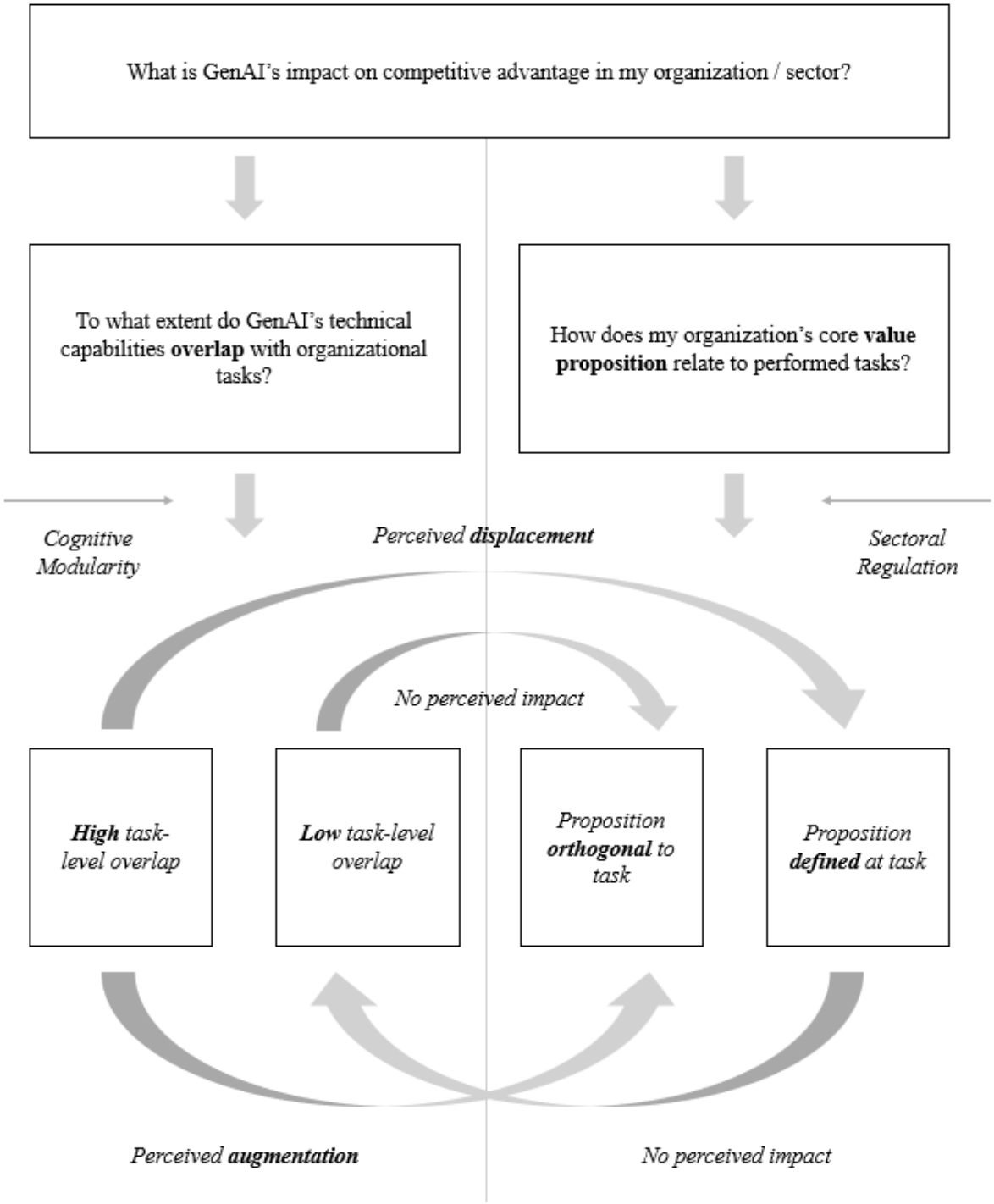
## 6.2 Findings and Implications

Our Stage 3 design, with executives assigned to roundtables based on variables such as pattern-recognition importance and proprietary data importance, enabled systematic observation of intra-sectoral differences. By comparing executives from similar sectors who diverged on key factors, we isolated the influence of these variables on perceptions of GenAI's impact. By matching participants' Stage 3 roundtable contributions with their Stage 2 survey responses, we could observe patterns in how organizational characteristics influenced executive perceptions.

The key finding of our abduction is that executives perceive the disruptive impact of GenAI through its relation to their business's value-add—the fundamental value they provide to customers—rather than through the overlap of functional tasks that GenAI can perform. When this value proposition aligned closely with GenAI-addressable tasks, executives perceived greater displacement threat. Conversely, when the value proposition was viewed as orthogonal to these tasks, executives perceived GenAI primarily as complementary. Law firm partners who saw their value proposition as resolving routine legal matters with established precedents expressed significantly greater concerns about displacement. In contrast, law firm partners who perceived their strategic value as resolving complex litigation through bespoke solutions and nuanced interpretations of the law viewed GenAI as merely augmenting their existing capabilities. Similarly, consulting firm directors emphasizing the provision of data-informed insights as their core value proposition perceived higher displacement risk than those defining their proposition around stakeholder alignment and hypothesis validation[2]. As a consulting executive (A2b) noted, "Most of our clients know what solution they want to implement. They come to us for external validation and to help build consensus among stakeholders. The CEO might be convinced, but they need us to help justify difficult decisions to the board or to align the executive team […] ChatGPT cannot do that." See Figure 2 for an illustration of our core finding.

[2] This observation is consistent with the agency-economics view that third-party monitors—auditors, outside directors, and management consultants—are hired either to certify decisions or to supply problem-solving expertise when principals and agents face information gaps (Alchian and Demsetz, 1972; Fama, 1980; Jensen and Meckling, 1976). Relatedly, a recent working paper has documented the marginal impact of episodic engagements of consulting firms on firm profitability (Bijnens, Jäger, and Schoefer, 2025).

**Figure 2: Directors' perceptual framework for assessing GenAI's organizational/sectoral impact**




This core finding was complemented by three additional yet related observations. First, certain sectors were naturally perceived to have value propositions more aligned with modular tasks that GenAI could perform well. In these sectors, there was high perceptual alignment among executives about GenAI's relationship to their core business. PR executives who noted that their work predominantly involved drawing on prior press releases to reproduce their style

recognized a natural overlap with GenAI capabilities and consequently viewed GenAI as having high displacement potential. Similarly, advertising executives uniformly acknowledged the threat to creative content generation, noting that clients would likely be unable to distinguish between human and AI-generated output. This explains certain inter-sectoral average differences—some sectors simply have perceived value propositions that naturally align more closely with the modular tasks that GenAI excels at performing.

Second, we identified regulatory buffer effects in executive perceptions. Executives in heavily regulated industries expressed comparatively far less concern over displacement, since they saw their core value proposition as intrinsically tied to the regulatory framework itself. Financial services executives emphasized that clients hired them specifically for the guarantee their services provided—a function GenAI cannot replicate. Legal executives similarly argued that while GenAI could perform document review efficiently, their primary proposition was providing regulatory certainty and assuming liability for advice rendered. Insurance executives stressed that their value proposition centered on regulatory-mandated accuracy, noting that "financials need precision, and AI has a habit of being drastically wrong." The contrast between regulated and non-regulated professional services was particularly stark. Despite describing similar task functions, executives in regulated service firms exhibited markedly different concerns about displacement compared to their counterparts in non-regulated service environments.

Third, differing perceptions of firms' value propositions directly impacted which complementary assets executives believed would bundle with GenAI to create further differentiation. This created divergent investment pathways even within the same sector. Executives who saw their primary value-add to customers as providing data-driven insights emphasized proprietary data repositories as crucial differentiators. Conversely, executives within the same sectors who defined their value through relationship management or contextual understanding emphasized tacit knowledge and relational capital as key complementary assets. These divergent perceptions influenced the barriers to which executives were paying attention. Law firm partners who saw their value as providing bespoke expertise expressed concern about how GenAI would affect their partner promotion structure, as the tasks being automated would displace traditional mechanisms by which junior lawyers climbed the corporate ladder. Similarly, in sectors where tacit knowledge was seen as central to value propositions, executives focused on how employees would acquire such knowledge if certain learning-by-doing tasks were automated. Manufacturing executives, for example, described concerns about maintaining apprenticeship models that had traditionally transferred tacit knowledge once routine processes were automated. Online Appendix Section D provides a comprehensive outline of all complementary assets and sectoral features that executives cited as relating to both threat of displacement and differentiation potential.

# 7. Additional Analyses

Our findings face three potential limitations that merit investigation. First, given the rapid advancement of GenAI capabilities and intensified public discourse since our original study, what we captured may represent a temporal snapshot that has since evolved. Second, directors' conceptualizations of their firms' value propositions may diverge from how their firms actually operate and differentiate themselves in practice. Third, our findings may lack generalizability beyond the IoD membership. The following sections outline how we systematically attempt to address each of these concerns; full details are in Online Appendix Section E, F, G, and H.

## 7.1 Have Executive Perceptions Changed over Time?

We re-administered a modified version of our Stage 2 survey to IoD members in June 2025, achieving 41 complete responses (19.4%) from executives who had participated in our original study. The survey instrument retained core constructs while incorporating additional items to capture evolving GenAI capabilities and market discourse. Perceptions of displacement and task alignment remained consistent with our Stage 3 observations. Crucially, we included a question asking executives to rank their respective value propositions, where we found consistency with statements during Stage 3. Only four directors showed inconsistencies, one of whose firms had dissolved by July 2025.

We conducted 12 follow-up one-on-one interviews with survey respondents from this June 2025 survey. These interviews confirmed that despite advancements in the technology, their perceptions of firm displacement and underlying rationale remained the same. As one accounting director noted: "We've already seen automation wipe out junior roles […]. But when clients come to [our firm], they want assurance. They want to know they won't get fined. That their circumstances have been properly considered. That value […] that's where [our firm] comes in."

## 7.2 Do Directors' Value Proposition Perceptions Align with Reality?

To assess whether executives' self-reported value proposition distinctiveness corresponded to objective measures of strategic positioning, we developed Strategic Differentiation Scores (SDS) following Guzman and Li's (2023) methodology for measuring differentiation in firm propositions. We retrieved website snapshots from the Internet Archive's Wayback Machine for firms represented in our Stage 3 sample, capturing data annually from 2022 through 2025. Using doc2vec embedding models, we calculated cosine similarity distances between each firm's website content and that of industry peers, with higher distances indicating greater strategic differentiation.

We successfully matched 127 executives from Stage 3 to their firms' SDS scores, representing 77.9% of our roundtable participants. The remaining firms lacked sufficient Wayback Machine snapshots for robust analysis and were removed. Strategic differentiation proved relatively stable across the analyzed period, with mean SDS scores varying by less than 0.05 annually

from 2023 to 2024. We observed modest increases in differentiation for certain firms in 2024 and 2025, with 31 companies (34.8% of our sample) showing SDS increases of more than 0.10 during this period, potentially reflecting repositioning, though we acknowledge this may not be related to GenAI.

We find that SDS scores align well with how executives in Stage 3 reported their value propositions, with those noting more distinct value propositions having corporate websites that also communicate more distinct positioning. We triangulated findings using LinkedIn business descriptions, finding high alignment between SDS scores and differentiated LinkedIn descriptions. While we cannot rule out that directors *incorrectly* perceive why customers value them, we have strong evidence suggesting that directors' perceptions are aligned with how their firms market themselves online to customers and clients, and that these scores are relatively stable over time.

## 7.3 Do Our Findings Hold Outside the IoD Sample?

While we believe we already addressed external validity concerns through our two additional roundtables with non-IoD members in our original 2024 study, we conducted an additional out-of-sample assessment nonetheless. We organized a roundtable in June 2025 with 27 director-level executives from knowledge-work industries under Chatham House rules. Twenty-five of these participants had no prior IoD affiliation and were recruited through professional networks.

Using similar prompts and scenarios to those in our Stage 3 roundtables, the out-of-sample executives demonstrated results consistent with our original findings. They showed strong consensus on GenAI's task-level capabilities while exhibiting marked heterogeneity in displacement expectations. Most significantly, the relationship between value proposition framing and displacement expectations was largely replicated: executives who defined their core value through GenAI-addressable tasks consistently expressed higher displacement concerns than those emphasizing relationship management, liability provision, or contextual judgment.

The consistency of findings across our three additional analyses strengthens confidence in the core conclusions. Executive perceptions of GenAI's disruptive potential appear to reflect stable cognitive frameworks rather than transient reactions to technological hype, correspond meaningfully to objective measures of strategic positioning, and generalize beyond our initial empirical setting. These results support our central claim that value proposition framing, rather than task-level capability, drives executive perceptions of GenAI's organizational impact. Comprehensive methodological details, complete statistical analyses, and extended discussion of these three validation studies are provided in the online appendix.

# 8. Discussion

It is now well established that GenAI possesses superior capabilities across many organizational tasks (Brynjolfsson *et al.*, 2025, 2025; Dell'Acqua *et al.*, 2023; Noy and Zhang, 2023). While these findings and task-based exposure measures (Brynjolfsson *et al.*, 2018; Eloundou *et al.*, 2024; Felten *et al.*, 2021; Handa *et al.*, 2025) indicate where productivity gains may emerge, our study reveals they do not necessarily predict where industry disruption will occur.

We build on the rich tradition that emphasizes the central role of executive perceptions in determining organizational responses to technological change (Eggers and Kaplan, 2009; Eggers and Park, 2018; Henderson and Clark, 1990; Ocasio, 2011; Tripsas and Gavetti, 2000). While this cognitive perspective has proven crucial for understanding incumbent responses to technological change, existing work has not systematically examined how executives' conceptualizations of their firms' value propositions—as distinct from task inventories—mediate their interpretations of an emerging technology's disruptive potential. Our mixed-methods abductive study of UK executives provides a complementary lens to the task-based framework in bridging the relationship between task-level capability overlap and competitive outcomes.

Our key finding is that executives evaluate GenAI's disruptive impact through its relation to their business's value proposition rather than through task-level overlap. When executives perceive their value proposition as aligned with GenAI-addressable tasks, they anticipate greater displacement threat; when viewed as orthogonal to these tasks, they see GenAI as complementary. This explains why occupational exposure measures offer limited insight into competitive dynamics: they do not account for how executives interpret GenAI's capabilities relative to their specific business context. Unlike task-based analyses that treat organizations as modular bundles of tasks, our findings reveal that the less modular executives perceive their firms to be, the less concerned they are about GenAI displacement. Several implications follow from our results[3].

Firstly, our empirical findings qualify some of the emerging discussion on GenAI's potential for "wholesale" displacement (Candelon *et al.*, 2025; Mollick, 2024). We find that executives often anchor their evaluations of displacement risk at the sectoral level, guided by shared institutional features—especially sector-level regulation, which codifies liability, assurance, and compliance roles that GenAI is not perceived to affect. At the same time, we observe substantial variation within sectors. This heterogeneity arises from how executives perceive of their firms' modularity: those who decompose their value propositions into tasks closely aligned with GenAI capabilities (e.g., pattern recognition or content generation) express greater concern over

[3] It's worth examining how task-level analyses using occupational data may systematically underrepresent firm value propositions that executives in our study identified. For instance, O*NET data for the occupation of "lawyers" comprises 22 tasks and 14 detailed work activities. However, we find limited representation of what some of our lawyer respondents described as their core value add: e.g., *serving as a liability shield*. Similarly, O*NET descriptions for "management analysts" contain 11 primary tasks but notably omit the *stakeholder alignment* and *hypothesis validation* functions that consulting executives in our study emphasized as central to their firms' value propositions. As Eloundou et al. (2024: Appendix A3.3.3) acknowledge, "it is still unclear to what extent occupations can be entirely broken down into tasks, and whether this approach systematically omits certain categories of skills or tasks that are tacitly required for competent performance of a job." While Bick et al. (2024) find that exposure indices derived from O*NET data correlate with actual GenAI adoption patterns in the workforce, our findings suggest that the mechanisms governing perceptions of disruption may operate at a different level than what task-based data currently captures.

displacement, while those who view their value as arising from integrated or orthogonal functions identify complementary assets they believe protect their position.

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. These perceptions are significant precisely because they may shape the very technological trajectories and competitive landscapes they anticipate (Acemoglu and Johnson, 2023). Rather than treating GenAI as an exogenous force with predetermined impacts, our study acknowledges that these executive perceptions will actively construct the competitive realities that emerge as firms allocate resources, develop capabilities, and position themselves strategically in response to their understanding of GenAI's potential. Incumbent perceptions may thus drive what value propositions *entrants* may choose to fit their shifting context. This, in turn raises fascinating questions about the perceptual dynamics and potential perceptual misalignment between firms in such quickly shifting contexts (see Thatchenkery and Piezunka, 2025).

Finally, our findings indicate that a task-based perspective, which primarily focuses on whether GenAI displaces or augments specific tasks, while useful, is insufficient for understanding the full industry-level implications of this technology. Much of the excitement over GenAI (Boussioux *et al.*, 2024; Dell'Acqua *et al.*, 2023; Eloundou *et al.*, 2024; Handa *et al.*, 2025; 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.*, 2025; or creating a new footwear strategy, as in Dell'Acqua *et al.*, 2023)—a limitation under increasing scrutiny (Brynjolfsson, 2022; Narayanan and Kapoor, 2024). By drawing on a foundational insight of strategic management research, into how firms survive technological discontinuities through the mediating role of managerial cognition, we provide a necessary complement to task-based approaches to begin unpacking how technological capabilities translate into competitive outcomes.

## 8.1 Theoretical Implications

Our study contributes to several literature streams in strategic management. First, we address a well-known limitation in existing firm 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). This dual nature makes it particularly challenging to apply traditional frameworks of technological change, which typically categorize innovations as either competency-enhancing or competency-destroying (Henderson and Clark, 1990; Tripsas, 1997; Tushman and Anderson, 1986). By examining executives' perceptions of how GenAI relates to their firms' value propositions, we

identify specific mechanisms that determine how and where executives perceive GenAI as enhancing and/or destroying competencies within their particular context.

The theoretical novelty of our approach lies in our examination of executive cognition during the emergent phase of a transformative technology. By studying how executives are making sense of this nascent yet extensively anticipated technology, we capture perceptions without the survivorship bias that often characterizes retrospective studies of technological adaptation (Eggers and Park, 2018). Our methodology allows us to document the real-time cognitive processes through which executives not only interpret GenAI's potential impact on their competitive positioning but actively construct the competitive landscape through their perceptions. These cognitive frames and resulting actions may collectively determine which designs become dominant and which applications emerge as "killers" (Anderson and Tushman, 1990; Suárez and Utterback, 1995), rather than executives merely responding to predetermined technological trajectories.

Perhaps most theoretically significant is our finding that executives' assessments of emergent technologies are fundamentally shaped by their perceptions of business modularity (Baldwin, 2024). Within the same sector, we observe striking heterogeneity in how executives define the boundaries of their core value proposition and, consequently, in how they interpret a technology's relationship to that proposition. This heterogeneity reflects different mental models of how executives compartmentalize what their organizations do. Some perceive their operations as highly decomposable into discrete functional components that align with technology-addressable tasks, while others within the same sector conceptualize their value-add as an integrated system inherently resistant to modular technological substitution. We are uniquely positioned to observe these divergent frames precisely because the technology we are studying operates at various levels of task granularity and can be deployed across multiple organizational interfaces (Handa *et al.*, 2025; McAfee, 2024). The cognitive variance in how executives perceive of their operations' modularity explains the divergent perceptions of displacement threat and differentiation potential that we observe, even among firms facing ostensibly similar competitive environments. Though our focus is on executives' *perceptions* of modularity, we expect that these are rooted in, though not perfectly reflective of, underlying organizational realities (Baldwin, 2024; MacDuffie, 2013). Consequentially, such perceptions by Directors also shape organizational responses and actions.

Our analysis also enriches our understanding of technological adaptation by highlighting the role of *value proposition conceptualization* as a mediating factor between task-level technological capabilities and industry-level outcomes. Traditional theories of technological change have often focused on either task-level automation potential (Autor *et al.*, 2003) or industry-level disruption (Christensen, 1997), with limited attention to the mechanisms that connect these levels of analysis. Our study serves as a systematic effort to bridge this gap by demonstrating how executives' interpretations of their value propositions filter their assessments of technological impact, resulting in heterogeneous strategic responses even within sectors.

Separately, our identification of sectoral "buffers" contributes to the literature on complementary assets and appropriability regimes (Breschi, Malerba, and Orsenigo, 2000; Jacobides *et al.*, 2021; Teece, 1986: 19; Winter, 1984). We find that regulatory requirements, liability frameworks, and institutionalized behavioral conservatism are perceived as important buffers

against disruption in certain sectors, moderating executives' perceptions (and, possibly, reality) of displacement threat.

We also show that even if GenAI is considered a general-purpose technology (Bresnahan, 2024; McAfee, 2024), its transformative impact is contingent upon its combination with other organizational elements and sectoral characteristics. By examining how different executives perceive these combinations, we contribute to theories of technological diffusion and adaptation by highlighting the heterogeneity in anticipated cognitive pathways through which a single technology may reshape competitive dynamics within and across sectors. For a technology that offers multi-purpose capabilities with relatively low deployment costs (McAfee, 2024), the significant variation in executive perceptions we document suggests that the diffusion and impact of GenAI may follow more complex and varied trajectories than previous GPTs.

## 8.2 Implications for Organizations and Policy

Our findings entail several implications for organizational strategy. First, inasmuch as perceptions align with reality, our findings suggest that organizations seeking to respond to GenAI disruption must consider how *value propositions* are positioned within their sectors. Our evidence suggests that some value propositions are perceived to be at risk of displacement while others are perceived to be safe. Second, our findings connect executives' perceptions of disruption with perceptions of the modularity of their business operations—the extent to which their value proposition can be unbundled. This suggests that executives may need to temper any enthusiasm on how modularity enables easier integration of GenAI with an understanding that modularity increases the risks of displacement. Third, our results suggest that select incumbents perceive their industry's structural characteristics—particularly regulatory frameworks, liability requirements, and institutional norms—to provide meaningful buffers against GenAI-driven disruption. This is why executives in regulated sectors perceive their organizations as having less-displaceable, non-task-based value propositions. This, though, may need to be balanced against the risk that their sector's natural protection might be challenged by new forms of competition, such as new value propositions (Ali *et al.*, 2023).

For policymakers, our findings carry several implications. First, the regulatory buffer effect described by respondents suggests that regulation may fundamentally shape how disruptive GenAI proves to be across sectors. Rather than viewing regulation as uniformly impeding innovation, policymakers should recognize how regulatory frameworks can provide stability during periods of technological transition by institutionalizing roles that emphasize human accountability and liability—functions that GenAI cannot readily replicate. Regulation may not only impede GenAI use; it also affects who will be affected and how. Second, our findings suggest that GenAI's impact will be heterogeneous both across and within sectors, driven not only by technology but also managerial cognition, the nature of value propositions, and regulation. This means that regulators may be able to affect the level and nature of GenAI impact by focusing on sector-specific features as they combine with technology to drive input. Policies may thus need to be more sector-specific.

## 8.3 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 GenAI adoption rates.

As with any study of technology's impact, especially in such a fast-moving context, we also face the risk of presenting results that will soon be obsolete. While our additional analyses conducted one year on suggest that our core thesis has remained remarkably robust, this may change in the future. We thus hope that our endeavor, which was to identify the cognitive mechanisms through which executives interpret emerging technologies (such as GenAI) and to study how these interpretations shape strategic responses, will stand the test of time.

Our methodology also comes with the risk of selection bias in our survey responses. The sample may over-represent executives who are more engaged with GenAI, potentially affecting the generalizability of our findings. This potential bias is partially mitigated, if not fully addressed, by the composition of our sample, which is predominantly drawn from knowledge-intensive sectors that are frequently cited as being particularly susceptible to GenAI-driven displacement. Also, the heterogeneity we observe in perceptions among this potentially engaged sample strengthens confidence in our core findings about the role of value proposition framing.

Additional limitations of our study's empirical context 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 how value proposition framing evolves as GenAI capabilities advance; and exploring whether our findings hold across different cultural and institutional contexts. Future research could also examine the accuracy of executives' value proposition assessments by studying customer perceptions and market outcomes. Additionally, longitudinal studies could investigate how the relationship between value proposition framing and displacement expectations changes as GenAI capabilities evolve and organizational experience with the technology deepens.

Limitations aside, our study highlights factors that go beyond tasks or occupations that influence disruption expectations, focusing on cognitive frames through which executives interpret their value propositions. The ways in which executives frame technologies help explain why executives in the same sector arrive at very different assessments of GenAI's disruptive potential, despite converging on task-level impact. We also highlight the importance of factors that complement GenAI (perceptions of) modularity, regulation and liability. Our work is complementary to these important task-based approaches, and we hope it provides a mid-range theory to begin dialogue about the mediating mechanisms between task-level capabilities and industry-level outcomes.

In all, our study provides a complementary lens to task-based approaches for understanding the relationship between GenAI's task-level capabilities and firm and sector-level change. By

examining how executives perceive GenAI in relation to their business's value proposition—rather than through task-level capabilities alone—we provide evidence suggesting that the path from technological capability to industry disruption is far from straightforward. As GenAI continues to evolve, our research underscores the need for a context-specific approach that recognizes the critical interplay between technological capabilities, value proposition framing, and sector-level structural features. Our findings suggest that disruption is not synonymous with task-level exposure—a crucial distinction for both research and practice. By providing an empirically grounded framework that bridges task-level capabilities and industry-level outcomes through the mediating role of executive cognition, our study sets the foundation for future research exploring how GenAI's capabilities translate into broader competitive outcomes.

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# Appendix

## Appendix A: Stage 1 Roundtables Insights

### A1. Roundtable Composition and Insights on GenAI Adoption Patterns

Table A1 describes the participant composition of our Stage 1 roundtables.

**Table A1: 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 |

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. Figure B1 presents an illustration of differences in sectoral averages.

**Figure B1. Expected importance of GenAI by sector: industry vs. organizational level**

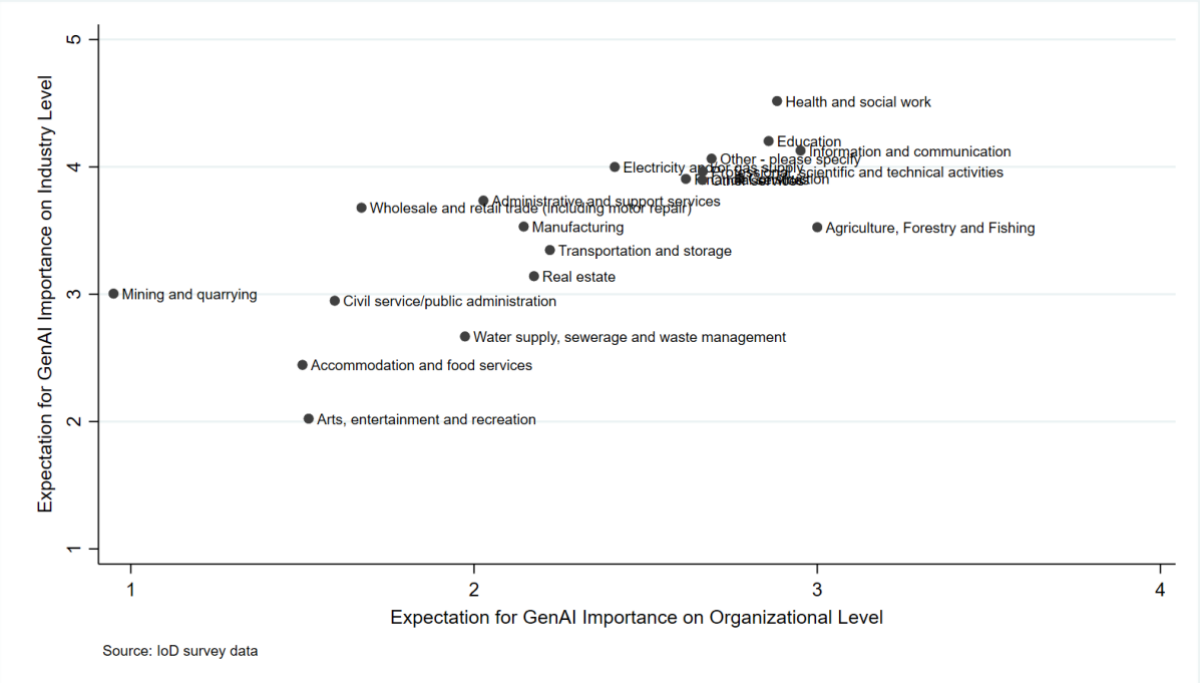


Table B3 presents expectations for GenAI within respondents' own organizations. Notably, 84.75% of executives anticipate some meaningful change, with 40.36% expecting operational efficiency gains, 23.32% foreseeing strategic transformation, and 21.08% predicting business-model reinvention. In contrast, 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.

Nonetheless, we acknowledge several methodological considerations that inform the interpretation of these findings. 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. Nonetheless, we hold that the consistent patterns between Stage 1 and 2 justify our Stage 3 investigation.

### 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)<br>[.043] | 0.816 (0.081)<br>[.040] | 0.822 (0.081)<br>[.047] |
| Regulation | 1.286 (0.175)<br>[.064] | 1.367 (0.195)<br>[.028] | 1.531 (0.223)<br>[.003] |
| Modularity | 1.350 (0.273)<br>[.139] | 2.028 (0.421)<br>[.001] | 1.841 (0.388)<br>[.004] |
| Output accuracy | 0.922 (0.126)<br>[.552] | 0.975 (0.136)<br>[.854] | 1.062 (0.146)<br>[.660] |
| Leadership disinterest | 0.740 (0.103)<br>[.030] | 0.431 (0.064)<br>[.000] | 0.647 (0.088)<br>[.001] |
| IP concerns | 1.185 (0.155)<br>[.193] | 1.232 (0.169)<br>[.128] | 1.098 (0.148)<br>[.489] |
| Financial cost | 0.736 (0.110)<br>[.041] | 0.774 (0.122)<br>[.105] | 0.905 (0.138)<br>[.512] |
| Strategic uncertainty | 1.244 (0.204)<br>[.185] | 1.115 (0.189)<br>[.523] | 0.951 (0.155)<br>[.759] |
| Staffing | 0.911 (0.128)<br>[.509] | 1.540 (0.239)<br>[.005] | 1.167 (0.174)<br>[.300] |
| Compliance | 0.770 (0.099)<br>[.042] | 0.996 (0.135)<br>[.977] | 0.828 (0.110)<br>[.156] |
| LR$\chi^2$ | 31.09<br>[.000] | 60.24<br>[.000] | 36.62<br>[.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)<br>[.006] | 1.074 (0.097)<br>[.429] | 0.804 (0.076)<br>[.020] |
| Regulation | 1.198 (0.162)<br>[.182] | 0.891 (0.116)<br>[.376] | 1.279 (0.182)<br>[.083] |
| Modularity | 1.046 (0.214)<br>[.827] | 0.839 (0.171)<br>[.388] | 1.537 (0.330)<br>[.045] |
| Proprietary data | 1.307 (0.161)<br>[.030] | 0.825 (0.100)<br>[.113] | 1.135 (0.320)<br>[.320] |
| Technical knowledge | 1.070 (0.178)<br>[.685] | 0.977 (0.159)<br>[.885] | 1.166 (0.201)<br>[.374] |
| Tacit knowledge | 1.454 (0.301)<br>[.071] | 1.178 (0.246)<br>[.432] | 1.081 (0.223)<br>[.705] |
| Pattern recognition | 1.510 (0.195)<br>[.001] | 1.045 (0.129)<br>[.719] | 1.293 (0.170)<br>[.051] |
| Market insight | 1.334 (0.232)<br>[.097] | 0.810 (0.134)<br>[.204] | 1.304 (0.227)<br>[.126] |
| Relational knowledge | 0.553 (0.108)<br>[.002] | 0.837 (0.154)<br>[.334] | 1.087 (0.204)<br>[.655] |
| LR$\chi^2$ | 52.56<br>[.000] | 11.61<br>[.236] | 42.56<br>[.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. Preface & Roundtable Compositions

This appendix provides detailed supporting information for how executives' understanding of their business role shapes their perceptions of displacement threat, potential for competitive advantage, and expectations of industry disruption. When executives perceive their business role as closely aligned with GenAI-addressable tasks, they express greater concern about displacement; when they see their role as orthogonal to these capabilities, they view GenAI primarily as complementary. The roundtable discussions and participant quotes captured here reveal the underlying mechanisms through which business role perception moderates the relationship between task-level capabilities and industry-level outcomes.

Table D1 provides a comprehensive overview of the nine roundtables conducted in Stage 3 of our research. The roundtables were strategically designed to explore various aspects of GenAI's impact following our abductive enquiry. Part A comprised seven paired roundtables (A1a-A4), each focusing on specific variables identified in Stage 2. These variables included pattern recognition importance, proprietary data importance, strategic uncertainty, and modularity. Part B comprised two separate roundtables (B1-B2) to provide 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.

**Table D1: Descriptives of Stage 3 roundtable participants**

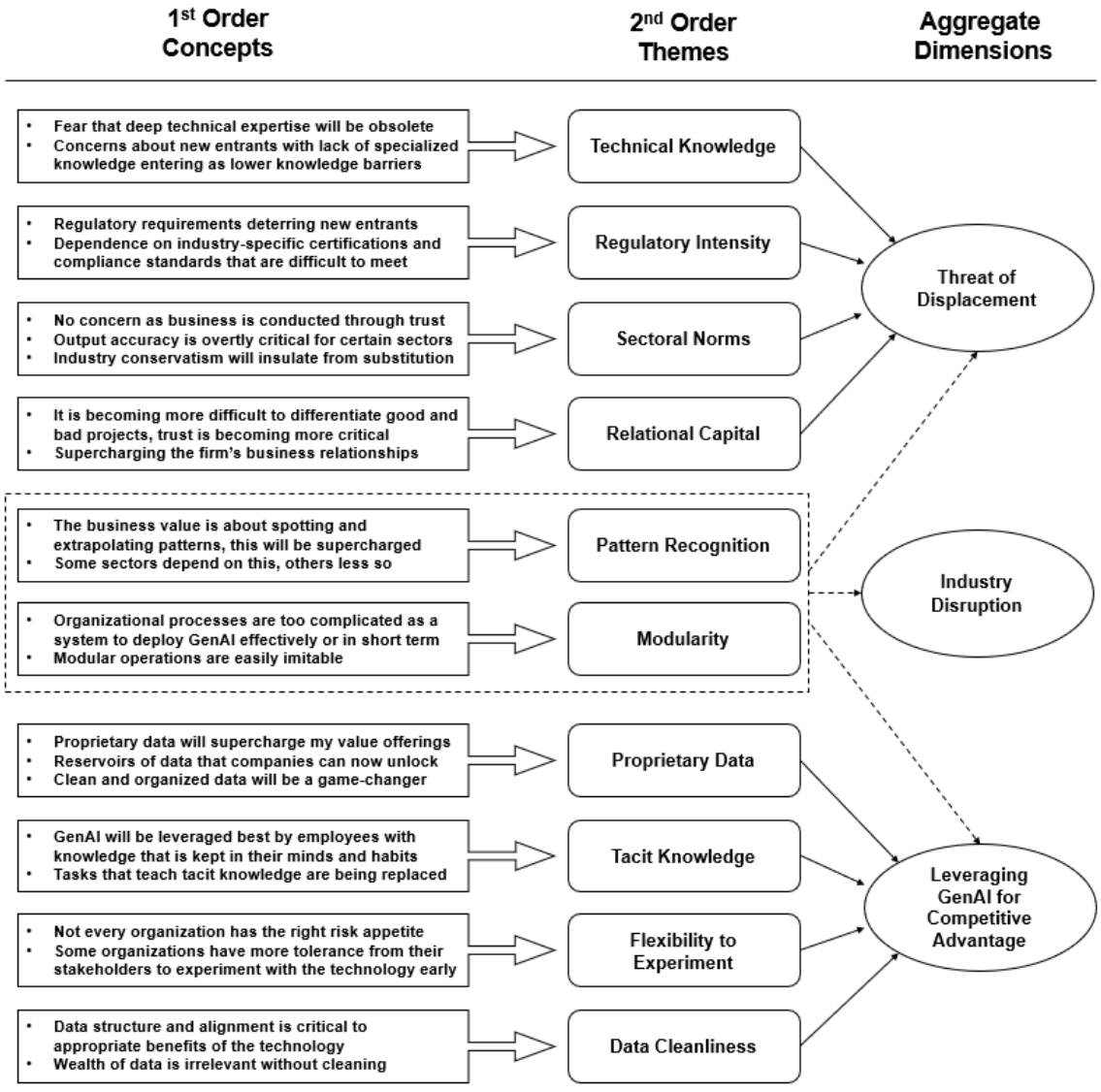
| # | Theme | Participants | Industry Coverage |
|---|---|---|---|
| A1a | High pattern recognition importance | 23 | Pharmaceuticals, biotechnology, cybersecurity, insurance, management consulting, ESG assessments, behavioral science, environmental planning and landscape design |
| A1b | Low pattern 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 |

The table details the number of participants in each roundtable and industry sectors represented. This information contextualizes the diverse perspectives captured in our study. Additionally, the table highlights the key characteristics of each roundtable, such as whether it focused on high or low levels of a particular variable.

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 allowed us to triangulate findings and develop understanding of how variables interacted to shape executives' perceptions of GenAI's impact on their organizations and industries.

Following transcription, we employed qualitative coding methodologies (Charmaz, 2006; Gioia, Corley, and Hamilton, 2013) to analyze the roundtable data. We used open coding to identify first-order concepts from informants' own words (Guba and Lincoln, 1982), then employed axial coding to develop higher-level themes, ultimately aggregating these into broader theoretical dimensions (Gioia and Chittipeddi, 1991). This iterative analytical approach allowed us to identify the emergent patterns that form the basis of our findings.

**Figure D1. Thematic coding from first-order concepts to aggregate dimensions**



## D2. 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 find that executives' perceptions of GenAI's disruptive impact are fundamentally shaped by how they conceptualize their business's core value proposition - the essential value they provide to customers. When GenAI capabilities align closely with this core value proposition, executives perceive greater displacement threat; when they view their value proposition as orthogonal to GenAI capabilities, they perceive GenAI primarily as complementary. This value proposition conceptualization influences perceptions of (1) displacement threat, (2) differentiation potential, and (3) overall industry disruption expectations.

## Part 1: Business Roles & Perceived Threat of Displacement

Our analysis revealed that executives conceptualize their value propositions in different ways that significantly influence their perception of displacement threat from GenAI. Four primary value proposition conceptualizations emerged from our data: regulatory intermediation, provision of output accuracy, relationship management, and technical expertise.

### Regulatory intermediation

Executives who defined their core value proposition as navigating regulatory frameworks and ensuring compliance perceived a substantially lower threat of displacement. In these contexts, the value is intrinsically tied to the regulatory environment itself, creating a buffer against GenAI displacement:

> **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.

Executives in highly regulated sectors highlighted that their core value involves the assumption of legal liability - a function that GenAI cannot replicate:

> **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 executives noted that outside consultants often misunderstood the centrality of regulatory compliance to their value proposition:

> **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.

### Provision of Output Accuracy

Executives who conceptualized their value proposition as delivering high-precision, accurate outputs perceived their offering as inherently resistant to GenAI displacement. These executives emphasized how their business success depends on consistently producing results with minimal error margins:

> **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.

In sectors where output accuracy is non-negotiable, executives perceived significant barriers to GenAI adoption due to current technological limitations in ensuring consistent precision:

> **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.

### Relational management

Executives who defined their core value proposition as managing and developing client relationships perceived less threat from GenAI displacement. These executives viewed their primary value as creating and maintaining interpersonal connections and trust that GenAI cannot replicate:

> **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.

These executives recognized that while GenAI might enhance efficiency in knowledge-oriented tasks, the human elements of building trust, managing expectations, and navigating interpersonal dynamics remained central to their value proposition and largely beyond GenAI's current capabilities.

### Technical expertise

Executives who conceptualized their value proposition primarily as providing technical expertise and specialized knowledge perceived a substantially higher threat of displacement from GenAI. These executives recognized that GenAI's capabilities overlap significantly with their core value:

> **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 (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.

Some executives in knowledge-oriented firms showed a nuanced understanding of which aspects of their value proposition were susceptible to displacement and which 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.

These observations highlight how executives who define their core value proposition primarily as providing technical expertise perceive a much higher threat of displacement from GenAI, prompting many to reconsider their fundamental value offering:

> **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: Business Roles & GenAI-Bundled Differentiation

Our analysis revealed that executives perceived certain business value propositions as particularly well-positioned to be enhanced by GenAI, creating opportunities for competitive differentiation. Three primary value propositions emerged as having strong potential for GenAI-based enhancement: proprietary data-driven insights, human judgment-centered services, and innovation-focused offerings.

### Proprietary data-driven insights

Executives who defined their core value proposition around delivering proprietary data-driven insights perceived significant opportunities to enhance this value through GenAI. These executives anticipated that GenAI could amplify their existing proprietary data assets to create superior insights and solutions:

> **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.

Professional services executives in particular reported a dawning realization that their historical client engagements represented a largely untapped reservoir that GenAI could help them leverage::

> **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.

As executives considered how GenAI might enhance their data-driven value propositions, many recognized that data cleanliness would be a critical moderating factor:

> **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.

In sectors with complex legacy systems and regulatory constraints, these concerns about data accessibility were particularly pronounced:

> **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.

### Human judgement-centered services

Executives who defined their value proposition around delivering superior human judgment and tacit expertise perceived opportunities to enhance this value by using GenAI to augment rather

than replace human capabilities. These executives emphasized how GenAI could help their experts focus on higher-level judgment tasks:

> **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.

Interestingly, these same executives expressed concern about how GenAI might disrupt traditional pathways for developing the human judgment that remains central to their value proposition:

> **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 executives see GenAI as potentially enhancing their judgment-centered value propositions, they worry the technology may simultaneously undermine the development of the very capability they seek to enhance.

Some executives pointed to challenges in defining exactly what human judgment entails in their context:

> **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 […].

### Experimentation Capacity

Executives who defined their value proposition around their organization's capacity to experiment and adapt saw significant opportunities to enhance this value through GenAI. These executives emphasized how their existing orientation toward flexibility and experimentation positioned them to leverage GenAI for competitive advantage:

> **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.

These executives viewed their experimentation capacity not merely as an organizational attribute but as a core value proposition that GenAI could significantly enhance. They anticipated that GenAI would accelerate their ability to explore novel solutions and approaches, further distinguishing them from more rigid competitors.

However, executives emphasized that this experimentation capacity could not be easily developed overnight:

> **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.

Executives who defined their value proposition around experimentation were particularly conscious of how legacy structures could impede their ability to fully leverage GenAI:

> **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.

These insights suggest that firms with experimentation-focused value propositions may be particularly well-positioned to create differentiation through GenAI, potentially widening the gap between themselves and competitors who lack this orientation.

## Part 3: Value Propositions & Perceptions of Overall Sectoral Disruption

This section explores how executives' perceptions of GenAI's impact vary based on how they define their core business role and value proposition to customers. We focus on two distinct business roles that emerged as particularly salient in our analysis: (1) pattern recognition as a central value-adding function, and (2) modularity in business process architecture. When executives view their core business role as primarily delivering pattern recognition value to clients, they perceive greater displacement threat from GenAI. Similarly, when they define their organizational structure as highly modular, they anticipate more significant disruption potential from GenAI.

### Pattern recognition

When executives defined their organization's core value proposition as centered on pattern recognition - the ability to identify, interpret, and exploit recurring structures or trends in data, processes, or phenomena that provide value to customers - their perceptions of GenAI's disruptive potential were significantly heightened. Our roundtable discussions with executives who rated pattern recognition as central to their business success (A1a, n = 23) versus those who rated it as peripheral (A1b, n = 13) revealed striking differences in perceived threats and opportunities.

Executives whose business role centered on delivering pattern recognition value to clients expressed substantial concern over GenAI's potential to replace human-driven pattern-recognition functions:

> **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.

In contrast, executives who positioned their business value outside of pattern recognition showed minimal apprehension about GenAI's disruptive potential:

> **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.

This divergence extended to how executives viewed GenAI's potential to create competitive differentiation. Those who defined their business role around pattern recognition saw GenAI as a transformative tool that could fundamentally enhance their core value proposition:

> **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 […]."

By contrast, executives whose business roles were less centered on pattern recognition primarily framed GenAI as offering incremental operational improvements:

> **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.

The implications for industry-level disruption similarly varied based on executives' perception of their business role. When pattern recognition was central to their value proposition, executives consistently articulated scenarios of substantial industry transformation driven by GenAI:

> **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.

Conversely, when pattern recognition was peripheral to their value proposition, executives 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.

## Modularity

The degree of modularity in an organization's business architecture emerged as another key dimension through which executives interpreted GenAI's potential impact. Modularity refers to the extent to which a firm's business processes, services, or products can be separated, recombined, and operated independently (Baldwin and Clark, 2000). Organizations that define their value proposition around highly modular business architectures perceive both greater displacement threat and greater differentiation potential from GenAI.

To investigate this further, we conducted a roundtable with a mix of respondents who reported high organizational modularity (n = 8) and low modularity (n = 7). Executives from highly modular organizations consistently perceived greater vulnerability to GenAI-driven displacement:

> **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 (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.

In contrast, executives from less modular organizations, where value is delivered through tightly integrated systems, expressed less concern about GenAI's displacement potential:

> **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.

Simultaneously, executives who defined their business architecture as highly modular saw greater potential to leverage GenAI for competitive advantage:

> **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.

Executives from less modular organizations, however, primarily viewed GenAI as offering incremental improvements rather than transformative potential:

> **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. Executives who defined their business architecture as highly modular anticipated more radical industry transformation:

> **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.

> **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 […].

In contrast, executives from less modular organizations expected more gradual industry evolution:

> **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.

While the current section contains condensed versions of certain quotes, Table D2 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 D2. Coded constructs and example roundtable quotes

| Variable | Full Quote |
|---|---|
| Regulatory Intermediation | "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."<br><br>"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."<br><br>"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."<br><br>"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." |
| Relational Management | 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 Expertise | "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]?"<br><br>"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."<br><br>"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." |

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| | "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."<br><br>"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-driven insights | "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."<br><br>"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."<br><br>"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."<br><br>"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." |
| Human judgement-centered services | "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."<br><br>"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." |

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| | "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."<br><br>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]. [...]<br><br>"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." |
| Experimentation Capacity | "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."<br><br>"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."<br><br>"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."<br><br>"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

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| | 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."<br><br>"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."<br><br>"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."<br><br>"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."<br><br>"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."<br><br>"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."<br><br>"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."<br><br>"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."<br><br>"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.'" |

| | |
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| | "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."<br><br>"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." |

## Appendix E: Additional Analyses – June 2025 Survey

### E1. Second Round Survey

Following formal consent from the Institute of Directors, we re-contacted participants from our original Stage 2 survey, leveraging the contact details we had collected in 2024. We emailed all eligible directors with a personalized link to a follow-up survey in June 2025, inviting them to reflect on their organization's value proposition and the role of GenAI. Of the total outreach, 19 respondents failed to complete the survey and were excluded. An additional three responses were removed after failing an attention check, leaving us with 41 complete and valid responses. For each respondent, we verified their sector and firm size using LinkedIn data, achieving a 100% match rate. Based on reported employee count, we confirmed size and used LinkedIn and public records to ensure firm continuity. These 41 responses serve as the basis for our descriptive analyses.

To triangulate the survey responses with prior qualitative data, we compared each respondent's 2025 survey answers with their Stage 3 roundtable articulations. We observed a high degree of consistency. Only four directors displayed divergence between what they articulated in the roundtables and what they subsequently ranked in the survey (e.g., in Q9 rating "technical expertise" low as a core value in the survey despite having emphasized it during the roundtable). In one of these four cases, the respondent's firm had dissolved by July 2025, and no information was publicly available explaining the dissolution. These comparisons increase confidence that respondents' value proposition perceptions have remained stable over the intervening year, suggesting that the roundtable format elicited durable cognitive frames. Given that it is unlikely for participants to recall their prior statements from a year ago, the strong alignment reinforces the methodological strength of our roundtable design in capturing executive perspectives.

#### Table E1 Distribution of respondents by sector

| Sector | Freq. | Percent | Cum. |
|---|---|---|---|
| Accommodation and food services | 1 | 2.44 | 2.44 |
| Administrative and support services | 1 | 2.44 | 4.88 |
| Agriculture, Forestry and Fishing | 1 | 2.44 | 7.32 |
| Construction | 2 | 4.88 | 12.20 |
| Education | 3 | 7.32 | 19.51 |
| Financial services | 4 | 9.76 | 29.27 |
| Health and social work | 1 | 2.44 | 31.71 |
| Information and communication | 5 | 12.20 | 43.90 |
| Manufacturing | 3 | 7.32 | 51.22 |
| Other – please specify | 4 | 9.76 | 60.98 |
| Other services | 1 | 2.44 | 63.41 |
| Professional services | 11 | 26.83 | 90.24 |
| Real estate | 3 | 7.32 | 97.56 |
| Wholesale and retail trade | 1 | 2.44 | 100.00 |
| **Total** | **41** | **100.00** | |

In terms of sectoral representation (Table E1), the sample is weighted toward professional services, accounting for roughly one-quarter of respondents, followed by legal, financial services, and consulting. Firms of various sizes are represented across the sample, with a notable concentration of small and medium-sized enterprises (as defined by turnover). In Table E2, the most commonly cited value propositions were “technical expertise” (32%) and “relationship management” (22%). Only three respondents selected “process efficiency” and just two selected “creative output” as their firm’s primary value proposition. We therefore caution against interpreting statistical patterns within these columns due to the very limited number of cases.

### Table E2 Assessments of how respondent organizations primarily create customer value today

| | Primary way your organization creates customer value today [a] | | | | | |
|---|---|---|---|---|---|---|
| | Technical expertise | Relationship management | Compliance & risk | Innovation & insight | Process efficiency | Creative output |
| Total | 31.71% | 21.95% | 17.07% | 17.07% | 7.32% | 4.88% |
| Small firm [a] | 33.33% | 16.67% | 20.83% | 20.83% | 0.00% | 8.33% |
| Medium | 23.08% | 38.46% | 7.69% | 7.69% | 23.08% | 0.00% |
| Large | 50.00% | 0.00% | 25.00% | 25.00% | 0.00% | 0.00% |
| Low mod [c] | 31.25% | 31.25% | 18.75% | 12.50% | 6.26% | 0.00% |
| Med mod | 16.67% | 25.00% | 33.33% | 25.00% | 0.00% | 0.00% |
| High mod | 46.15% | 7.69% | 0.00% | 15.38% | 15.38% | 15.38% |

[a] Responses to Q8 (“Which **ONE** of the following best describes how your organization creates value for customers *today*?”)
[b] Responses to Q5 (“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 Q17 (“How **modular** are your organization’s core operating activities?”). Low modularity is defined as “Very Low Modularity” and “Low Modularity”, medium modularity as “Moderate Modularity”, high modularity as “High Modularity” and “Very High Modularity”

Table E3 asked respondents to indicate the extent to which GenAI is currently being used to support each type of value proposition within their organization. Rather than mapping to a single, self-identified core proposition, this question captures usage patterns across multiple value domains. The results show that GenAI is being most heavily used in areas related to “technical expertise” and “creative output,” with a majority of respondents reporting moderate to high usage in these domains. Usage is more limited in relation to “compliance and assurance” and “relationship management,” where many respondents indicated little to no current application.

### Table E3 Extent to which GenAI is being used for each value proposition today

| | Extent of GenAI use for each value proposition today [a] | | | | | |
|---|---|---|---|---|---|---|
| | Technical expertise | Relationship management | Compliance & risk | Innovation & insight | Process efficiency | Creative output |
| None at all | 26.83% | 51.22% | 53.66% | 34.15% | 34.15% | 36.59% |
| A little | 24.39% | 21.95% | 19.51% | 19.51% | 14.63% | 12.20% |
| Moderate | 19.51% | 7.32% | 9.76% | 12.20% | 21.95% | 21.95% |
| A lot | 21.95% | 17.07% | 9.76% | 21.95% | 12.20% | 19.51% |
| A great deal | 7.32% | 2.44% | 7.32% | 12.20% | 17.07% | 9.76% |

[a] Responses to Q9 ("Across each value proposition, to what extent does your organization **already use GenAI** in **delivering that value to customers**? ").

Table E4 presents executives' perceived risk of competitive advantage erosion under scenario where 90% of the firm's tasks were automated by AI. Respondents who cited "technical expertise" or "relationship management" were spread across the scale, with a tendency toward middle-range responses. Among those citing "innovation and insight," responses were more variable but skewed toward concern. The few cases in the "process efficiency" and "creative output" columns showed high perceived exposure, but again, the low sample size precludes meaningful interpretation.

### Table E4 Presuming significant task automation, competitive advantage erosion

| | 90% automation erosion [a] | | | | | |
|---|---|---|---|---|---|---|
| | Technical expertise [b] | Relationship management | Compliance & risk | Innovation & insight | Process efficiency | Creative output |
| No erosion | 15.38% | 22.22% | 14.29% | 28.57% | 0.00% | 0.00% |
| Minor erosion | 38.46% | 33.33% | 0.00% | 28.57% | 0.00% | 50.00% |
| Moderate erosion | 38.46% | 33.33% | 57.14% | 28.57% | 66.67% | 0.00% |
| Substantial erosion | 7.69% | 0.00% | 28.57% | 14.29% | 33.33% | 50.00% |
| Complete erosion | 0.00% | 11.11% | 0.00% | 0.00% | 0.00% | 0.00% |

[a] Responses to Q21 ("Imagine that within five years, Generative AI can fully automate 50% of the professional tasks currently performed across your industry. Under this scenario, to what extent do you believe your firm's competitive advantage would be eroded?").
[b] Responses to Q8 ("Which **ONE** of the following best describes how your organization creates value for customers *today*?")

Perceived likelihood of displacement (Table E5) also varied by value proposition. Respondents identifying "relationship management" or "compliance and assurance" largely viewed displacement as unlikely, with most selecting the lower end of the scale. Those citing "technical expertise" were more mixed. Expectations for GenAI-driven enhancement over the next five years (Table E6) showed the clearest pattern. Most directors who reported "technical expertise" or "innovation and insight" expected GenAI to enhance their firm's offering.

### Table E5 Likelihood of displacement in next 5 years based on core value proposition

| | Displacement likelihood given core value proposition [a] | | | | | |
|---|---|---|---|---|---|---|
| | Technical expertise [b] | Relationship management | Compliance & risk | Innovation & insight | Process efficiency | Creative output |
| Extremely unlikely | 38.46% | 33.33% | 14.29% | 14.29% | 0.00% | 0.00% |
| Somewhat unlikely | 15.38% | 22.22% | 57.14% | 42.86% | 66.67% | 50.00% |
| Neither / Neutral | 23.08% | 22.22% | 14.29% | 0.00% | 33.33% | 0.00% |
| Somewhat likely | 23.08% | 11.11% | 14.29% | 42.86% | 0.00% | 50.00% |
| Extremely likely | 0.00% | 11.11% | 0.00% | 0.00% | 0.00% | 0.00% |

[a] Responses to Q19 ("In the next 5 years, how likely is it that Generative AI could **replace your core offerings**? ").
[b] Responses to Q8 ("Which **ONE** of the following best describes how your organization creates value for customers *today*?")

Taken together, these descriptive results offer a snapshot of how directors currently view the relationship between GenAI and their firm's strategic positioning. What is particularly striking is the heterogeneity in how firms - especially those in professional services - frame their overall value proposition. Even within a single sector, respondents emphasize different sources of organizational value. This is further reflected in Question 9 of the survey, where respondents were asked to rank the relative importance of each value proposition to their firm. Some respondents placed technical expertise at the top of their value stack, others emphasized relationship management or stakeholder assurance. These patterns closely align with our Stage 3 roundtable observations, where intra-sectoral differences in displacement expectations corresponded intra-sectoral differences in perceived displacement. To further investigate what executives perceive to have changed in the year since our original study, we conducted a set of follow-up one-on-one interviews with willing respondents from the 2025 survey, as outlined in the next section.

### Table E6 Likelihood of enhancement in next 5 years based on core value proposition

| | Enhancement likelihood given value proposition [a] | | | | | |
|---|---|---|---|---|---|---|
| | Technical expertise [b] | Relationship management | Compliance & risk | Innovation & insight | Process efficiency | Creative output |
| Extremely unlikely | 7.69% | 22.22% | 14.29% | 0.00% | 0.00% | 0.00% |
| Somewhat unlikely | 15.38% | 11.11% | 14.29% | 0.00% | 0.00% | 0.00% |
| Neither / Neutral | 15.38% | 11.11% | 28.57% | 0.00% | 0.00% | 0.00% |
| Somewhat likely | 30.77% | 22.22% | 28.57% | 14.29% | 100.00% | 0.00% |
| Extremely likely | 30.77% | 33.33% | 14.29% | 85.71% | 0.00% | 100.00% |

[a] Responses to Q20 ("In the next 5 years, how likely is it that Generative AI could **enhance your core offerings**?").
[b] Responses to Q8 ("Which **ONE** of the following best describes how your organization creates value for customers *today*?")

## Appendix F: Additional Analyses – July 2025 Interviews

### F1. One on One Interviews with Survey Respondents

While our follow-up survey in June 2025 provided encouraging signs of perceptual stability - most notably the consistency in how executives ranked their firms' value propositions relative to our Stage 3 findings - we sought to probe more deeply into whether, and how, executives' views on GenAI displacement risk had evolved over time. Survey responses, while useful for identifying surface-level trends, could not fully capture the richness of directors' reasoning or reveal how they reconciled increasing GenAI capabilities with ongoing confidence in their firms' defensibility.

To address this, we conducted a series of 45-minute one-on-one interviews with executives who had indicated a willingness to be contacted for further participation. These interviews aimed to go beyond the quantitative instrument, offering an opportunity to explore apparent contradictions, deepen our understanding of mental models, and assess the durability of executives' narratives in the face of technological change. This qualitative stage allowed us to triangulate with earlier data, strengthen confidence in the interpretation of survey results, and explore whether any latent shifts had begun to take root. The sections that follow outline our interview protocol, participant demographics, and the main themes that emerged.

### F2. Interview Invite Protocol & Demographics

#### Recruitment Process

Interview participants were recruited through our survey instrument, which concluded with: "We may reach out for a short Zoom interview to explore your answers in more depth - your insights would be greatly helpful to our study. May we contact you?" Respondents could select "Yes" or "No, I prefer not to be contacted."

Of the 41 respondents who completed the full survey, 24 participants (58.5%) agreed to interviews. The research team then contacted these participants to schedule interviews within a two-week timeframe using a Doodle poll, explaining that responses would be anonymized and used solely for research purposes. Due to scheduling constraints, we successfully conducted interviews with 12 directors.

#### Participant Demographics and Sector Representation

Interview participants represented diverse knowledge-intensive sectors, including strategy consulting, financial services, technology consulting, construction, venture capital, legal services, and media & communications. This distribution provided insights across industries where generative AI applications and displacement concerns are particularly salient.

#### Interview Scheduling and Data Management Protocols

The authorship team contacted willing participants directly using survey-collected email addresses, thanking them for their participation and expressing our appreciation for their willingness to contribute further insights. Interview scheduling was coordinated through email and Doodle polls, with all sessions conducted via Zoom for accessibility.

Prior to each interview, explicit consent for recording was obtained from participants. We reiterated that all responses would be anonymized and used solely for research purposes, with assurances that individual responses would not be attributable to specific participants or organizations. Each session was recorded using Zoom and transcribed using encrypted software to ensure data security and participant privacy.

### Interview Preparation and Data Validation

The interviewer, a member of the authorship team, had access to each participant's original survey responses during the interview session. This enabled real-time verification of responses and allowed for clarification of any apparent discrepancies between survey answers and interview statements, enhancing the overall data quality and consistency of the research.

## F3. Interview Guide

**Introduction**: "Thank you for participating in this follow-up interview. Approximately one year ago, you completed a survey (*and if applicable,* joined us in our roundtables) as part of our research on GenAI and its implications for organizational work. Today, we are revisiting this topic to understand how your perspectives and experiences may have evolved over the past year. We are particularly interested in your observations and direct experiences with GenAI technologies within your organization and industry context. Please feel free to draw upon specific examples."

| **Theme 1: Organizational GenAI Adoption and Usage Patterns** | |
|---|---|
| **Main Questions** | **Probes** |
| How has GenAI usage evolved in your firm over the past year? | • Can you describe specific areas or functions where you've observed increased GenAI usage?<br>• What types of tasks has your organization begun using GenAI for that weren't being addressed a year ago? How about breadth or depth? |
| How aligned are GenAI capabilities with your firm's tasks? | • Can you provide examples of where alignment is strong/weak?<br>• How has this alignment changed over the past year? |
| **Theme 2: Perceptions of Task Displacement** | |
| How might GenAI displace activities that your firm currently performs? | • When you think about displacement, what aspects of your work come to mind?<br>• How do you distinguish between tasks that might be displaced versus those that might be augmented?<br>• What factors do you consider when evaluating displacement risk? |
| How might supplier or customer GenAI use affect your firm? | • Have you observed suppliers leveraging GenAI in ways that change their service delivery or pricing?<br>• If customers had direct access to similar GenAI tools, how might that alter their relationship with your organization? |

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| **Theme 3: Stakeholder Relationship Dynamics** | |
| How have customer interactions changed due to GenAI developments? | • Are customers making different demands or setting different expectations?<br>• Have you noticed changes in pricing pressures or negotiation dynamics?<br>• Can you identify any business gains or losses that seem related to GenAI developments? |
| *(If applicable)* How have supplier relationships evolved in the context of GenAI developments ? | • Are suppliers offering new services or changing existing ones due to GenAI?<br>• Have you seen shifts in supplier performance expectations or delivery standards?<br>• How has supplier GenAI adoption affected your procurement strategies? |
| **Theme 4: Task Overlap and Organizational Displacement** | |
| As GenAI capabilities strengthen, how does task overlap affect your firm's strategic positioning? | • What makes customers choose your organization over alternatives, and how might GenAI affect these differentiators?<br>• If you were to articulate your organization's value proposition today, how would it compare to a year ago?<br>• Which aspects of your value creation do you see as most vulnerable or most defensible against GenAI capabilities? |
| How do you reconcile task-level overlap with your firm's continued market relevance? | • When you think about the tasks where overlap exists, what explains your organization's continued advantage?<br>• Are there elements of your work that you believe GenAI cannot replace?<br>• How has your thinking about your firm's competitive moat evolved? |
| **Theme 5: Evolving Perceptions and Future Outlook** | |
| Have any experiences over the past year changed your views about GenAI's displacement potential? | • Can you describe a specific moment or realization that shifted your thinking?<br>• What role has media coverage or industry discourse played in shaping your perceptions?<br>• How have your direct experiences with the technology influenced your views? |
| How has your confidence in assessing GenAI capabilities changed? | • Are you more or less certain about the technology's limitations?<br>• What aspects of GenAI development do you feel you can predict versus those that remain uncertain? |
| What factors will determine whether GenAI displaces or augments your firm? | • What could happen for your displacement concerns to be realized?<br>• What developments might reinforce your organization's position? |

## F4. Interview Findings

To assess whether executive perceptions of displacement have shifted over time, we conducted 12 one-on-one follow-up interviews in July 2025 with directors who had participated in our follow-up survey. While all directors recognized that GenAI had become more capable over the past year - and had been adopted for an increasing array of tasks - there was striking stability in their core belief: that GenAI would not displace their firm's value proposition. These interviews consistently reaffirmed our central finding that executives interpret disruption not at the task level, but through their mental model of their firm's differentiated role in the market.

## Broad Agreement on Expanding Adoption and Capability Improvement

Each executive we interviewed noted that GenAI tools had become more embedded in day-to-day workflows and had improved significantly in accuracy, usability, and speed. Many emphasized their own evolving practices - adopting paid versions of ChatGPT or Copilot, integrating the tools into new functions, or building internal prompting protocols to enhance output quality. As two directors of a financial and legal consultancy explained:

> "*The efficiency gains are enormous. I had to digest 196 pages of legislation last week - I just dropped it into Copilot and had a structured summary in minutes. It's the kind of thing that used to take an entire weekend. But I still double-check everything. I don't just trust the output blindly*" (Director, Financial Consultancy).

> "*My workflow now is to record the conversation, run it through a transcription tool, clean it, and then paste it into ChatGPT. Within seconds, I get a summary that's 95% accurate. That used to take hours. It's changed how I prepare reports, design workshops, even structure client engagements*" (Director, Legal Advisory).

Others described using GenAI tools as a natural extension of internal search or research tasks. A director from an accounting firm noted:

> "*I use it for technical references, tax law, checking HMRC clauses. But you need to know what you're looking for - because the answer you get depends on how well you phrase the prompt. It's a great assistant, but it can't think for you*" (Director, Accounting Firm).

Executives across sectors, from marketing to professional services to education, described the technology as being faster, more reliable, and easier to integrate into operations than one year ago. A few highlighted how GenAI had accelerated team workflows and reduced reliance on external contractors or junior staff. Yet none described these improvements as altering their firm's core identity or proposition.

## Core Perceptions of Displacement Remain Unchanged

Despite these functional improvements, interviewees were clear that they did not see GenAI displacing what they understood to be their firm's unique contribution to customers. This was a near-universal view. Directors repeatedly emphasized that while tasks were being automated, the "value" they delivered was rooted in human interpretation, accountability, relational trust, or deep contextual understanding - features they did not believe GenAI could replicate.

The director of a B2B marketing agency with a focus on technically complex products noted:

> "*You can ask ChatGPT to write something about, say, caramelization processes in sugar engineering. But it won't know the proprietary methods our clients are using. That knowledge isn't online - it lives in the head of a food scientist. Our job is to extract it and translate it credibly. That's not something GenAI can do*" (Director, Marketing Agency).

Similarly, a director of an accountancy firm stressed that their value lay in tailoring interpretation to unique client contexts:

> "*We've already seen automation wipe out junior roles - bookkeeping, reconciliations, data entry. But when clients come to [our firm], they want assurance. They want to know they won't get fined. That their circumstances have been properly considered. That value […] that's where we come in*." (Director, Accounting Firm).

One executive emphasized that clients still expected a human to "own" the result:

> "*Even if GenAI writes the entire first draft of a report or workshop, I'm the one who puts my name on it. I'm the one the client is trusting to stand behind the message, the insight, the outcome. And that's not changing anytime soon*" (Director, Legal Advisory).

In regulated sectors, directors noted that their organizational role was often defined in part by law - as fiduciaries, certified professionals, or licensed overseers of risk - and thus unlikely to be undermined by technological capability alone. As one noted:

> "*Clients don't come to us for facts. They come for the confidence that the facts are being interpreted correctly, with responsibility and consequences. The penalties for getting it wrong are high. GenAI can't be sued, but we can*" (Director, Legal/Compliance Sector).

## Occupational Displacement Acknowledged, but Organizational Value Seen as Intact

Executives were much more open to the idea that individual roles - particularly junior or administrative ones - were at risk of being displaced or significantly restructured. Nearly all directors reported that automation had already led to headcount compression in certain areas.

An accounting director traced this trend over decades:

> *"When I first joined, we had six juniors doing tasks that one person now does. We've automated trial balances, accounts production, invoice capture, bank feeds - you name it. The work's disappeared from the bottom up. But the advisory and review layer, where risk and liability sit - that's where we still matter"* (Director, Accounting Firm).

A director of a veterinary education platform described how this was reshaping hiring strategies:

> *"We're not bringing in grads in the same numbers anymore. It's not because we don't need people - it's that AI is doing what they used to do. But the firm's proposition, what we offer vets in terms of certified CPD, is still human-verified, regulated, and differentiated. That hasn't changed"* (Director, Online Education/EdTech).

One director even acknowledged that his own role might eventually evolve or disappear:

> *"I sometimes think, you know, how long before I'm the one being automated? But then I think - what would clients be left with? A well-formatted answer, maybe. But not the judgment, not the liability, not the trust. That's still me. At least for now"* (Director, Strategy Consultancy).

This occupational versus organizational distinction was echoed across all of the 12 interviews. Executives were confident in forecasting job loss and structural changes - but did not believe that GenAI would fundamentally alter why customers choose to work with their firm.

## One Outlier: A Small Advisory Firm with Task-Defined Value

Only one director voiced genuine concern that GenAI may be displacing her firm's value proposition. A director from a boutique advisory business, acknowledged that clients were increasingly using GenAI to solve problems her firm previously handled manually.

> "*Clients used to come to us for help with sector research, building bid responses, putting together insight decks. Now they're doing a lot of that themselves with ChatGPT. They'll run a prompt, get something decent, and send it to us for light review - or not at all*" (Director, Boutique Advisory).

However, when asked to describe her firm's core value proposition, much of the language was in task-oriented terms: "helping clients summarize complex issues and propose solutions" – and noted great confidence that GenAI would displace her firm's position, and her sector's existence. Unlike other directors who emphasized accountability, liability, or relational trust as differentiators, this director described a narrower role grounded in information synthesis and formatting.

## Technological Improvement Did Not Alter Perceptions on Displacement

Finally, directors were asked whether any developments over the past year - or any imagined improvements in GenAI's future capabilities - might challenge their current views regarding displacement. While 5 directors mentioned being open to the idea in theory, in practice, they struggled to envision a scenario where this would occur.

> *"The hallucinations are lower, yes. The interfaces are slicker. But nothing I've seen changes the fundamentals. The human part is still central to what we offer*" (Director, Financial Consultancy).

> "*We've become much more efficient. But efficiency isn't disruption. It hasn't changed our value proposition. Our clients still need someone to think with, to trust, to stand behind the result*" (Director, Legal advisory).

> "*Unless we get to a point where AI is better than me at sensing what a client really needs - not just what they say - I don't see it replacing the relationship, the advisory intuition. That's still the moat*" (Director, Strategy Consultancy).

In short, executives were not dogmatic. They remained open to the possibility that their views could shift. But they emphasized that neither the capabilities they observed over the past year nor any plausible near-future improvement had altered their underlying mental model of value.

These 12 follow-up interviews reveal a high degree of stability in executive perceptions regarding displacement risk. Despite improved capabilities and increased use of GenAI across a broad range of tasks, directors overwhelmingly continued to view their organization's value proposition as insulated from substitution. Most distinguished sharply between task automation (which they embraced) and value displacement (which they rejected). They acknowledged occupational churn, particularly among junior and administrative roles, and a need for organizational adaptation. But they did not view these shifts as undermining the fundamental reason their firms existed.

## Appendix G: Additional Analyses – Wayback Machine Snapshots

### G1. Motivation for our additional analysis

One potential limitation of our original study is that what executives communicate in our Stage 3 roundtables may not accurately reflect how their firms actually market themselves to customers, or at least how customers perceive them. While our roundtables capture executives' internal conceptualizations of their firms' strategic positioning, there exists a possibility that these perceptions diverge from the value propositions their organizations actually communicate in the marketplace. This disconnect could arise from several factors: executives may have aspirational (misguided) views of their firms' differentiation that have not yet been realized in practice, they may misunderstand what truly drives customer choice in their markets, or there may be organizational misalignment between strategic intent and market execution.

To partially address this concern, we attempt to validate whether directors' self-reported strategic positioning corresponds to objective, externally observable measures of how their firms differentiate themselves. This validation serves two purposes: first, it helps establish that our findings reflect genuine organizational positioning rather than merely executive perceptions, and second, it provides evidence that directors have accurate insights into their firms' competitive positioning - a critical assumption underlying our theoretical framework.

### G2. Capturing our sample's publicly marketed positioning

We followed the general logic of Guzman and Li (2023) who provide the starting method to measuring firm-level value proposition differentiation from Crunchbase startup websites close to their founding year. Though given their interest was for US startup and concerned with one year per firm, we adapted each step to the United Kingdom context and to our research purposes.

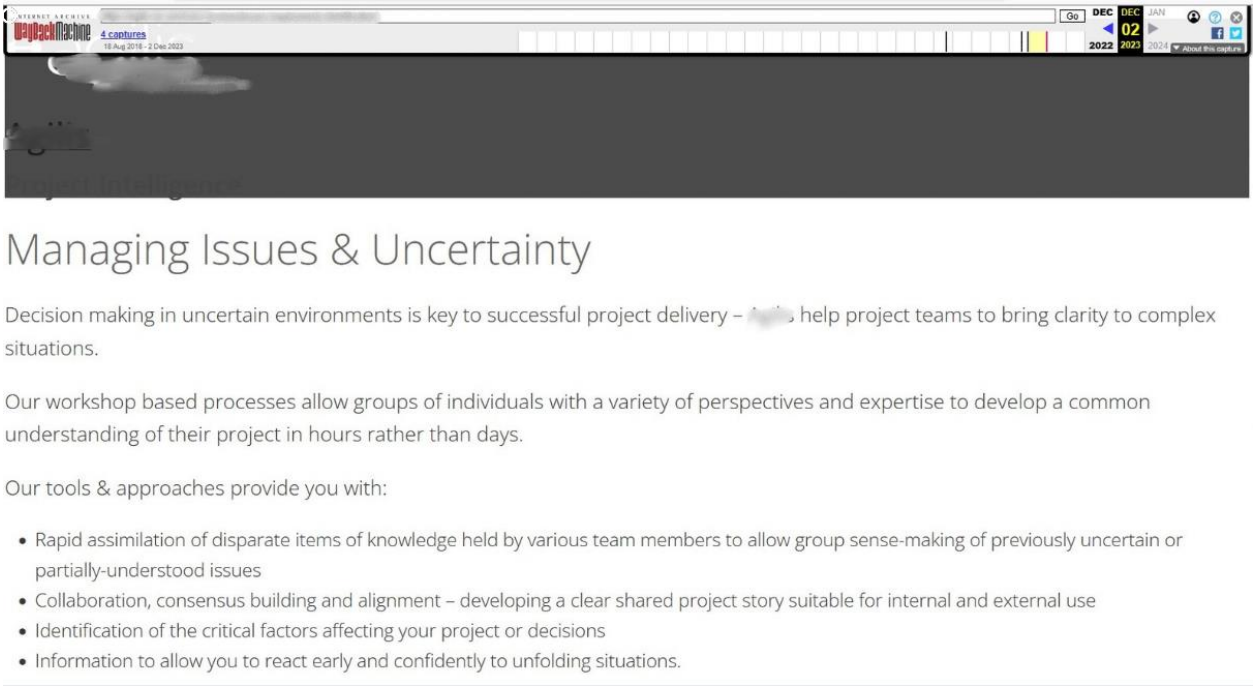
First, *website snapshots*. Using the Internet Archive's Wayback Machine we crawled the earliest clean homepage available for each firm in calendar years 2020 to 2025. Each download included up to ten internal links, stripped of boiler-plate and non-English text, yielding 927 firm-year documents (roughly 9100 tokens apiece).

Second, *semantic embeddings*. We trained a 700-dimension doc2vec model on the combined corpus and represented every firm-year as a single vector. Cosine distance measures the semantic gap between any two vectors.

Third, *industry classification* and *peer identification*. Because UK firms do not file 10-K statements, as per Guzman and Li's (2023) original approach, we created a multi-source classification pipeline. For 79 per cent of the firms a 4-digit Standard Industrial Classification code was taken directly from Companies House; these codes were cross-checked against industry assignments in the FAME database. Professional-services firms (legal, consulting, financial, accountancy) were additionally validated against sector directories such as Legal 500, the Management Consultancies Association roster and the FCA register. The residual set, for which no clear industry tag could be located, was assigned to clusters using the Hoberg-and-Phillips (2016) text-similarity algorithm applied to the firms' own website language.

Using these industry tags, we drew a comparison pool of more than 1,500 established UK organizations. For each focal firm, we analyzed snapshots from 2022 through 2025, excluding the COVID-19 pandemic years (2020-2021) to avoid potential distortions in firm positioning statements during this exceptional period. We use the 2024 snapshots as our primary cross-sectional analysis to match our focal study timing. For each focal firm in each year, we retained the five comparison firms whose website vectors lay nearest in embedding space; the mean of those five cosine distances is the SDS for that firm-year. A larger score therefore indicates a more distinctive value proposition. Figure G1 provides an illustration of a Wayback Machine snapshot.

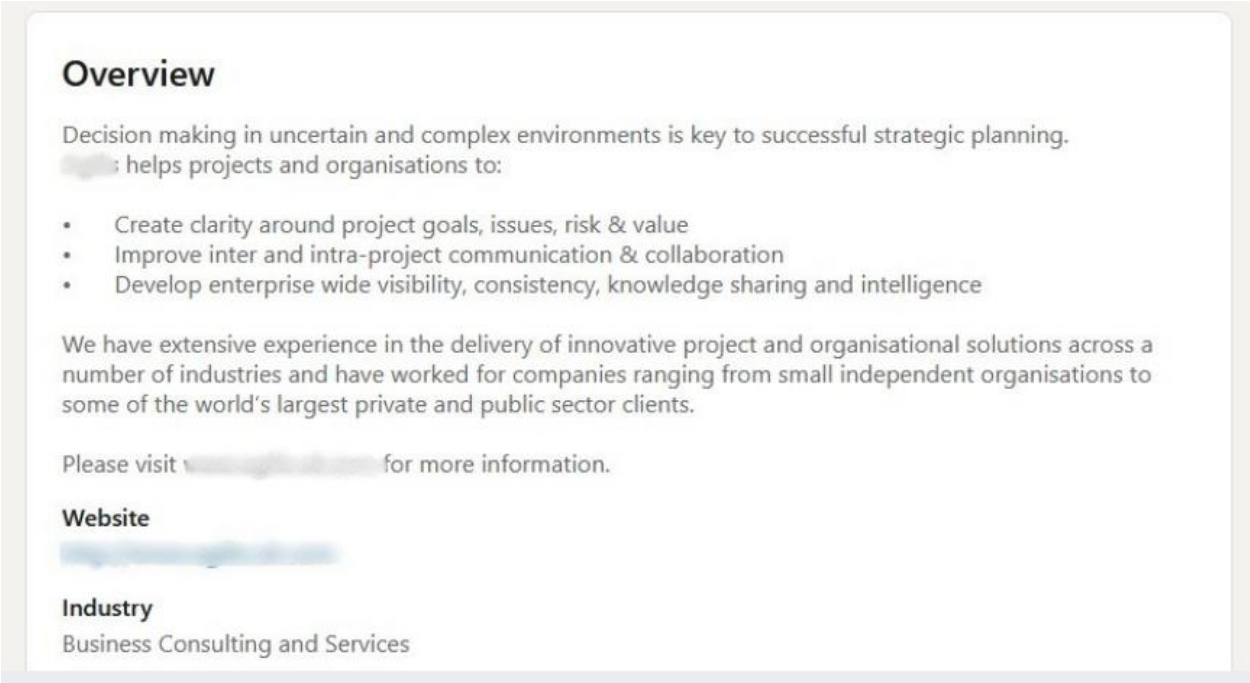
**Figure G1. Example of Wayback Machine Snapshot**




*Note*: The above illustrates one of the ten crawled pages within 2023 for one IoD sample firm, firm name blurred

Fourth, *triangulation with LinkedIn* data. To check that our measure of strategic differentiation scores was capturing what outsiders actually see, we scraped the business description that LinkedIn displays on every company's profile. An independent coder, blind to the SDS, classified each description as specialized or generic. Sixty-nine per cent of the firms that LinkedIn portrays as specialized fall in the top tercile of the SDS distribution, while only nineteen per cent of the generic descriptors do so, lending face validity to the measure. Figure G2 shows an example of a LinkedIn company descriptor used in the qualitative cross-check.

**Figure G2. Example of LinkedIn business description**

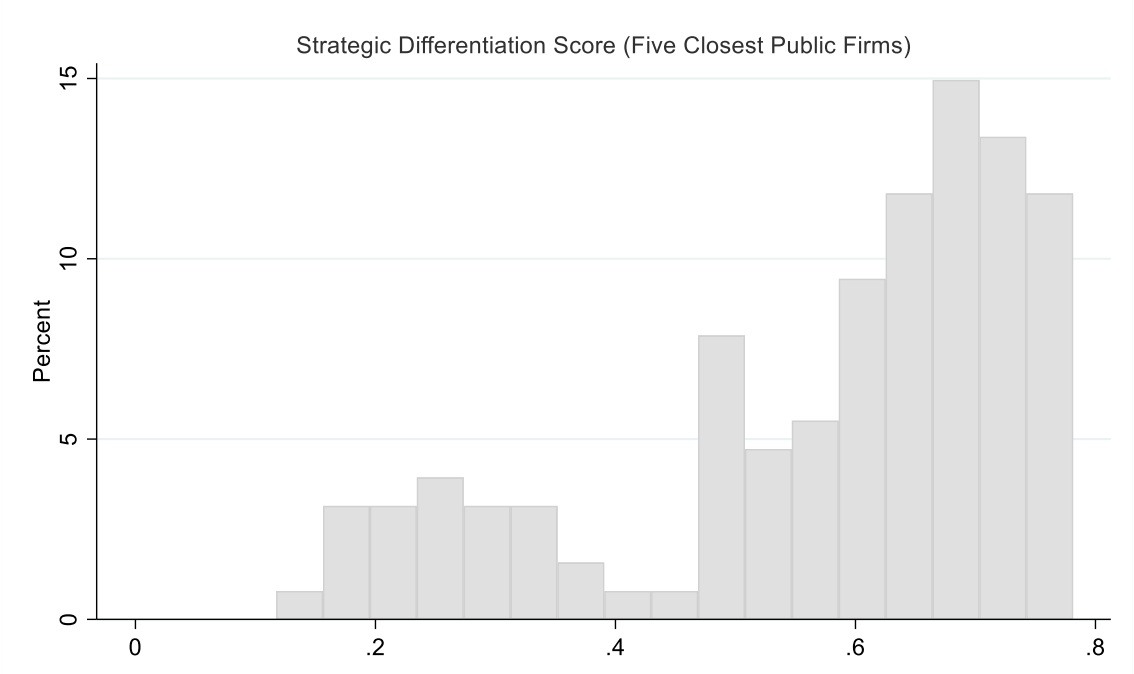



*Note*: The above illustrates one of the ten crawled pages within 2023 for one IoD sample firm, firm name blurred

## G3. Descriptive patterns

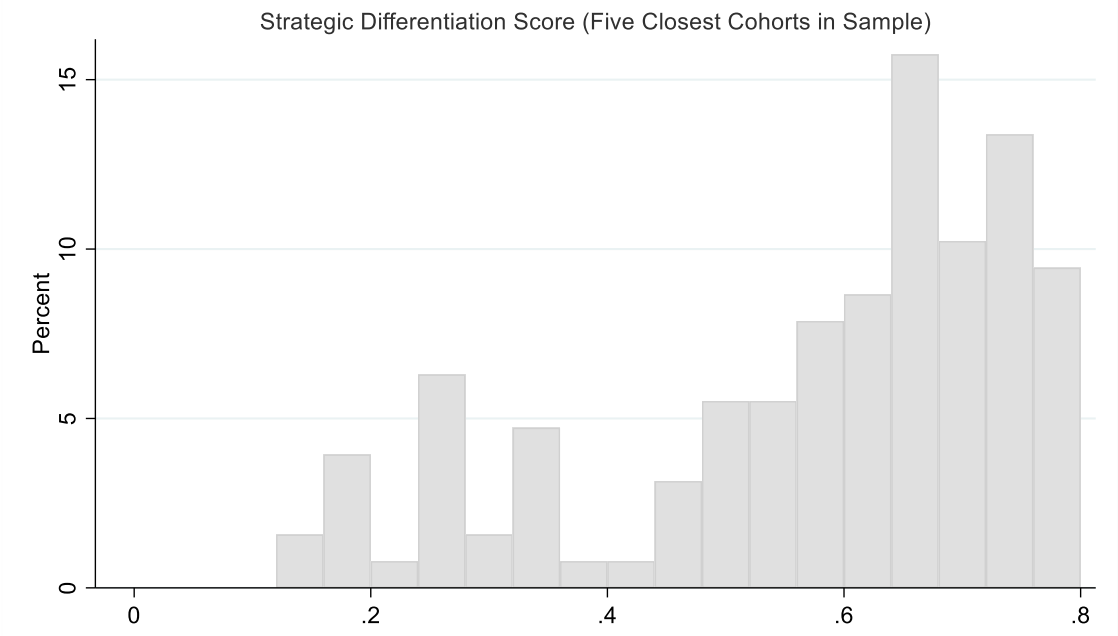
We were able to match 127 directors who participated in Stage 3 unambiguously to a firm, so the analysis covers the majority of the round-table sample. We take the 2024 cross-section to present our main results, but test for multiple firm-year find no meaningful differences. While some firm re-positioning occurs between 2024 and 2025, these represent minor changes in the SDS scores, suggesting that SDS is a relatively stable measure within our sample. Within our sampled firms, the SDS ranges from 0.14 to 0.78, with a mean of 0.57 and a standard deviation of 0.17. Roughly two-thirds of the firms score above 0.67, indicating that the modal director is indeed running an organization that markets itself as distinct, yet the left tail is substantive: about one in five firms post scores below 0.40, suggesting a markedly undifferentiated sub-group. When we examine the annual series, firm-level SDS is highly persistent; the correlation between the 2020 and 2025 values is 0.79, but eighteen per cent of the companies experience jumps or drops greater than 0.10.

## Figure G3. Distribution of Strategic Differentiation Score (5CP)



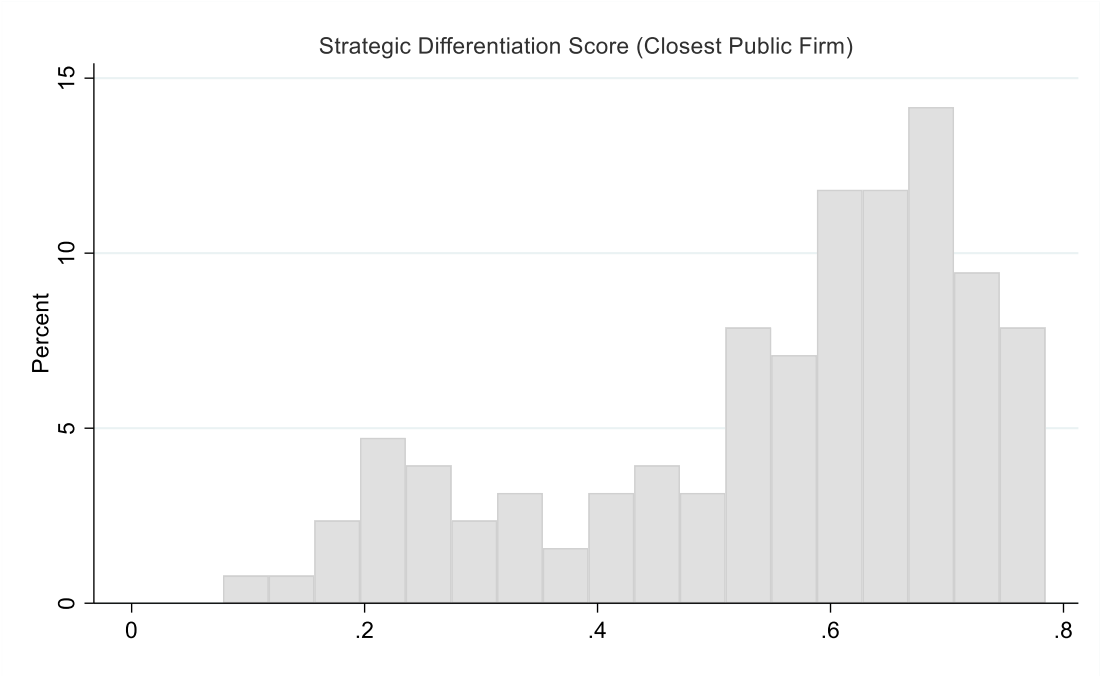

*Note*: Reports the histogram of strategic differentiation score (2024) estimated as the mean distance in the focal website for the five closest public firms as outlined in earlier methodology, estimated using word-embedding.

## Figure G4. Distribution of Strategic Differentiation Score (5CC)



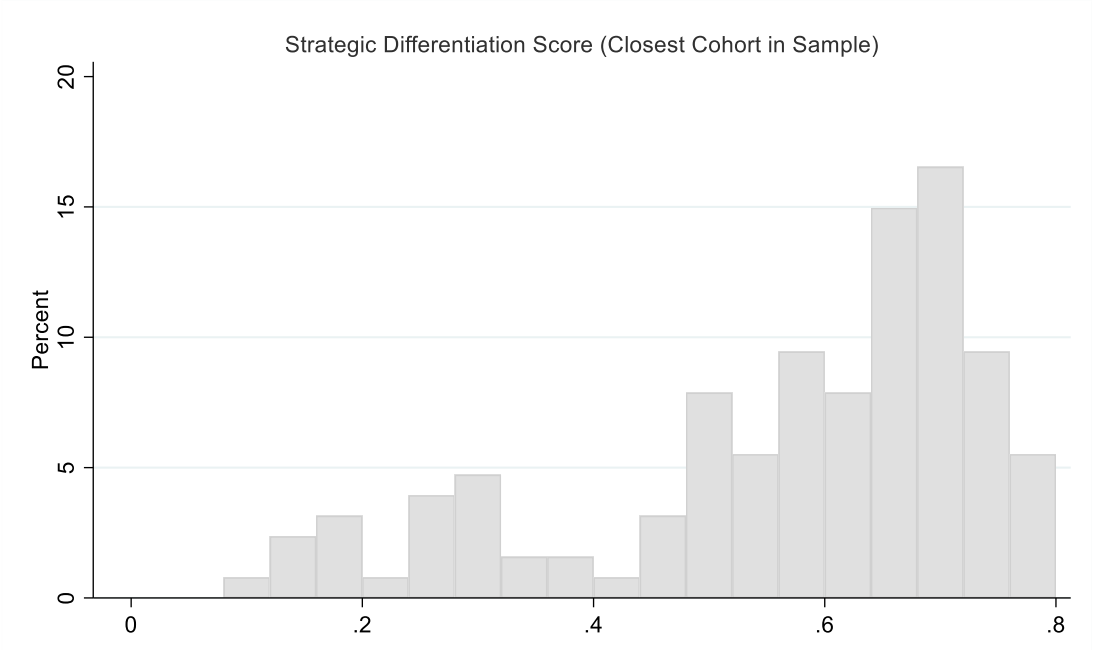

*Note*: Reports the histogram of strategic differentiation score (2024) estimated as mean distance in the focal website for the five closest firms within IoD sample as outlined in earlier methodology, estimated using word-embedding.

## Figure G5. Distribution of Strategic Differentiation Score (1CP)




*Note*: Reports the histogram of strategic differentiation score (2024) estimated as the mean distance in the focal website for the closest public firm as outlined in earlier methodology, estimated using word-embedding.

## Figure G6. Distribution of Strategic Differentiation Score (1CC)




*Note*: Reports the histogram of strategic differentiation score (2024) estimated as the mean distance in the focal website for closest cohort within IoD sample as outlined in earlier methodology, estimated using word-embedding

Directors whose round-table narratives we coded as “highly distinctive” have an average SDS seven hundredths of a point higher than their peers, a statistically and substantively meaningful difference. The alignment between spoken narratives and independently derived website distances therefore reassures us that our roundtable coding is capturing more than misaligned rhetoric.

To illustrate how our SDS scores map to the qualitative insights from Stage 3, consider two law firms from our sample. A firm scoring 0.71 (90th percentile) emphasized their value proposition as providing 'interpretive skill' and 'tacit knowledge' that AI cannot replicate, with one partner noting: 'Our skill is more in what you're calling tacit knowledge side of things. So, the know-how, more of an interpretive skill, the communication side of things.'

In contrast, a firm scoring 0.48 (10th percentile) acknowledged that “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, and it is a fear that we have 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..'

Similarly, in consulting, firms scoring around 0.70 emphasized stakeholder alignment ('Most of our clients know what solution they want... They need us to help build consensus among stakeholders... ChatGPT cannot do that'), while those around 0.55 focused on pattern recognition capabilities that GenAI could replicate.

Figures G3 through G6 plot, respectively, the 2024 distributions of: (i) the SDS relative to the five closest public comparison firms; (ii) the SDS relative to the five nearest peers drawn only from the IoD cohort; (iii) the distance to the single closest public comparison firm; and (iv) the distance to the single closest IoD cohort peer. All four histograms reproduce the right-skewed shape described above and demonstrate that the bulk of the mass lies above the mid-point of the 0.10-to-0.80 scale.

## Appendix H: Additional Analyses – June 2025 Roundtable

### H1. Roundtable (June 2025) to Test Out of Sample Validity

We conducted an out-of-sample validation roundtable on June 30, 2025, hosted at the authors' business school premises to examine whether our core findings extended beyond the IoD membership. The session lasted approximately 5 hours and brought together 27 director-level executives from primarily knowledge-work industries, with 25 participants (92.6%) having no prior IoD affiliation. Participants were recruited through professional networks to ensure independence from our original sample.

The roundtable followed a structured format comprising three main segments. The first segment (approximately 90 minutes) focused on participants' direct experiences with GenAI implementation within their organizations. The second segment (2 hours) examined organizational adaptations already underway in response to GenAI capabilities. The final segment (90 minutes) explored anticipated future adaptations and strategic positioning. This structure allowed us to capture both retrospective assessments and forward-looking expectations, mirroring the temporal dimensions explored in our original study.

#### Participant Composition and Organizational Representation

What distinguished this out-of-sample group was the exceptional seniority of participants, with many occupying C-suite or board-level positions that afforded them unique vantage points across multiple sectors. Their discussions were notably reflective, often incorporating buy-side perspectives and cross-sector evaluations that extended well beyond their own organizations' experiences. This multi-stakeholder perspective enriched our validation, as executives could compare and contrast GenAI's impact across their portfolios, client bases, and competitive landscapes.

The out-of-sample group exhibited notable diversity across organizational types and sectors. Participants included executives from global consulting firms, financial services companies (including banking and insurance), technology ventures backed by venture capital, healthcare organizations focused on vaccine development, news and media organizations, retail and consumer goods companies, logistics firms, and non-profit research institutions.

**Table H1. June 2025 Roundtable Composition[a]**

| Role / Position | Organization type | Category |
|---|---|---|
| Director of HR Strategy | Postal & Logistics | HR & People |
| Head of Western European Delivery | IT Services | Operations & Delivery |
| Chief Financial Officer | Technology Start-up | Finance Leadership |
| Principal & Ambassador | Management Consulting | Consulting Leadership |
| Head of R&D and Innovation | Consumer Goods | R&D & Innovation |
| Vice President of Research (AI) | AI Research Lab | AI & Data Leadership |
| Director, Retail & Consumer Sector | AI Consultancy | Strategy & Transformation |
| Senior Director, AI Research (Europe) | IT Services | AI & Data Leadership |
| Managing Director, AI | Private Equity | AI & Data Leadership |
| Professor; Lead Advisor | Academia | Academic & Consulting |
| Director of IT & Digital Transformation | Global Health Organization | Strategy & Transformation |
| Chief Executive Officer | Technology Lab | Executive Leadership |
| Researcher | Academia | Academic & Research |
| Research VP & Senior Research Director | Industry Research Firm | Industry Research |
| General Partner | Venture Capital | Investment & VC |
| Global Head of Data & AI Transformation | Financial Services | AI & Data Leadership |
| Principal & Ambassador | Management Consulting | Consulting Leadership |
| Engagement Manager | Leadership Advisory | Consulting Leadership |
| Head of Strategy & Excellence | Executive Search Firm | Strategy & Transformation |
| Chief Data Officer | Retail / E-commerce | AI & Data Leadership |
| Global Managing Editor, AI Newsroom | Media | Media & Comms |
| Chief Digital Officer, AI & Transformation | Investment Group | AI & Data Leadership |
| General Manager, People Analytics | Banking & Financial Services | HR & People |
| Head of AI | Insurance | AI & Data Leadership |
| Head of Innovation & Technology Policy | Policy Institute | Policy & Governance |
| Advisor | Venture Capital | Investment & VC |
| Director, AI Science Institute; VP Data Science | Management Consulting | AI & Data Leadership |

[a] The original invite list consisted of 30 individuals. Three dropped out on the day due to unforeseen circumstances.

Notably, several participants occupied boundary-spanning roles that offered unique perspectives on GenAI adoption across different organizational contexts. For instance, one participant led AI initiatives at a major insurance company while another directed digital transformation at a global vaccine development organization. Multiple venture capitalists provided insights into how AI-native companies were approaching market entry, while executives from traditional corporations offered perspectives on incumbent adaptation strategies.

## Replication of Core Findings

The roundtable discussions revealed patterns strikingly consistent with our original findings. Participants demonstrated strong consensus regarding GenAI's task-level capabilities while

exhibiting marked heterogeneity in their expectations of organizational displacement. As one executive from a management consulting firm noted, “GenAI is good at the task – and that’s not what disruption is about. Seeing firms as tasks misses the point.”

The relationship between value proposition framing and displacement expectations emerged organically in discussions. A participant from the insurance sector articulated this distinction clearly: financials need precision, and AI has a habit of being drastically wrong, emphasizing how their value proposition centered on regulatory-mandated accuracy rather than pattern recognition. Similarly, executives from heavily regulated sectors consistently expressed lower displacement concerns, attributing this to their role in providing legal liability and accountability - functions they perceived as beyond GenAI's reach.

## Sectoral Variations and Regulatory Buffers

Consistent with our original findings, executives from regulated industries demonstrated systematically different perceptions of GenAI's disruptive potential. Participants from financial services and healthcare emphasized how regulatory requirements created natural barriers to displacement. As articulated by multiple participants, these sectors' value propositions inherently involved certification and the assumption of legal liability - functions that regulatory frameworks preserve for human actors.

The roundtable also revealed how prior experiences with technological disruption shaped current responses. News and media executives, having witnessed social media ruin their business model, demonstrated heightened urgency in GenAI adoption compared to executives from sectors without such precedents.

## Emergence of Additional Insights

Beyond validating our core thesis, the out-of-sample roundtable surfaced several nuanced insights that enriched our understanding. Participants highlighted how generational differences within organizations shaped GenAI adoption patterns. As one participant noted about generational differences in technological familiarity: *I've got more AI experience than my management has. I've been using it since [I] first came out of university... I am an AI native*.

The discussion also revealed evolving market dynamics that reinforced our findings about heterogeneous impacts. Several participants described the emergence of "AI-native roll-ups" - ventures using AI to acquire and transform traditional service businesses. One venture capitalist detailed how these entities were buying up the company that actually does the work and achieving dramatic margin expansion through automation.

## Methodological Reflections

The consistency between our out-of-sample findings and original results strengthens confidence in our core theoretical contributions. Despite the different composition of participants and the passage of time since our original study, the fundamental relationship

between value proposition conceptualization and displacement expectations remained robust. Executives continued to evaluate GenAI's impact through the lens of their business's core value proposition rather than through task-level capabilities alone.

The roundtable format proved particularly effective for surfacing these dynamics. The peer-group setting enabled participants to articulate and debate their perspectives in ways that revealed underlying cognitive frameworks. When exposed to identical scenarios and prompts, executives from similar sectors but with different value proposition framings consistently diverged in their displacement expectations, precisely replicating the patterns observed in our original Stage 3 roundtables.

In conclusion, our out-of-sample validation provides strong evidence that our findings extend beyond the specific context of IoD membership. The replication of core patterns across a diverse group of non-IoD executives suggests that value proposition framing represents a fundamental mechanism through which executives interpret emerging technologies, rather than an artifact of our particular sample or methodology.

While we note the limitation that we cannot compare this sample of executives with their responses from the previous year (unlike our longitudinal analysis with the IoD sample), what this tells us is that the cognitive frameworks we identified are not merely stable within individuals over time but represent shared interpretive schemas that emerge independently across different executive populations. The replication of our core patterns among executives with no exposure to our original study suggests these frameworks reflect fundamental ways in which senior leaders make sense of technological disruption, rather than learned responses or sample-specific phenomena.

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