Generative AI Adoption and Business Performance in the United Kingdom: An Empirical Investigation of the Mediating Roles of Operational Efficiency and Product Innovation

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Abstract
Objective: This study provides an empirical analysis of the link between Generative AI (GenAI) adoption and business performance in UK firms, with a specific focus on the mediating effects of operational efficiency and product innovation.
Methodology: Grounded in the Resource-Based View (RBV) and the Technology-Organization-Environment (TOE) framework, a conceptual model was developed and tested. Data were collected via a cross-sectional survey of 312 senior managers across diverse UK industries. The data were analysed using partial least squares structural equation modeling (PLS-SEM).
Findings: The results indicate a significant positive direct relationship between GenAI adoption and business performance. Both operational efficiency and product innovation were found to be significant partial mediators, with product innovation exhibiting a stronger mediating effect. Key drivers of adoption included technological competence, top management support, and competitive pressure, while regulatory uncertainty was a significant barrier.
Implications: The findings offer robust evidence for policymakers and business leaders, positioning GenAI not just as a tool for cost reduction but as a strategic lever for growth, primarily through enhanced innovation. The study underscores the need for sustained investment in technological infrastructure and workforce skills.
Originality/Value: This research is one of the first large-scale quantitative studies to empirically validate the mediating pathways through which GenAI influences business performance, providing nuanced, context-specific insights for the UK market.

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Keywords: Generative AI, Business Performance, Operational Efficiency, Product Innovation, PLS-SEM, Resource-Based View

Introduction

The contemporary business environment is undergoing a profound transformation driven by artificial intelligence (AI). A particularly disruptive subset, Generative AI (GenAI), which specializes in creating novel content, code, and solutions, has captured significant scholarly and commercial interest (Brynjolfsson & McAfee, 2017) [4]. Models like GPT-4 and Midjourney are poised to redefine business processes in areas from marketing to software development (Davenport & Ronanki, 2018) [7]. The UK's National AI Strategy (UK Government, 2021) [23], which aims to establish the nation as a global AI leader, makes the investigation of GenAI's business implications particularly timely.

However, a considerable gap persists between the heralded potential of GenAI and rigorous empirical evidence detailing its impact on firm performance (Firk *et al.*, 2021) [9]. The current literature is rich in conceptual discussions and case studies (Borges *et al.*, 2021; Verhoeff *et al.*, 2021) [3, 24] but lacks large-scale quantitative studies that statistically delineate the mechanisms through which GenAI adoption translates into performance outcomes. This gap is critical; without empirical validation, business leaders lack a solid evidence base for strategic investment, and policymakers are ill-equipped to design effective support mechanisms. This study is guided by the following research question: What is the impact of generative AI adoption on the business performance of companies in the UK, and how is this relationship mediated by operational efficiency and product innovation? Anchored in the Resource-Based View (RBV) (Barney, 1991) [2], we conceptualize GenAI as a valuable, rare, and imperfectly imitable resource that enhances performance by bolstering operational capabilities (Wu *et al*., 2020) [27] and innovation capabilities (Nambisan *et al*., 2019) [17].

Furthermore, the Technology-Organisation-Environment (TOE) framework (Tornatzky & Fleischer, 1990) [22] is utilized to contextualize the drivers and barriers of GenAI adoption unique to the UK. This dual theoretical foundation enables a holistic examination of both the antecedents and consequences of GenAI adoption.

This research contributes to the academic discourse in several ways. First, it offers one of the first extensive empirical examinations of the GenAI-business performance link in a major economy. Second, it clarifies the underlying mechanisms by quantifying the mediating roles of operational efficiency and product innovation. Third, it provides a contextualized analysis of the UK business environment, identifying key adoption influencers. The findings are intended to yield practical recommendations for managers considering GenAI implementation and for policymakers crafting enabling environments for AI-driven growth.

Literature Review and Hypothesis Development

Theoretical Foundations

Resource-Based View (RBV): The RBV posits that sustainable competitive advantage stems from resources that are valuable, rare, inimitable, and non-substitutable (VRIN) (Barney, 1991) [2]. This study conceptualizes a firm's capacity to deploy Generative AI as a strategic resource bundle, encompassing the technology, its training data, and the human expertise required to leverage it (Borges *et al*., 2021) [3]. This GenAI capability, when integrated, augments other organizational capacities. We focus on two: operational capability, manifesting as efficiency (Wu *et al*., 2020) [27], and innovation capability (Nambisan *et al*., 2019) [17]. By automating complex cognitive tasks, generating novel ideas, and personalizing customer interactions, GenAI can significantly enhance both efficiency and innovation, thereby driving superior performance.

Technology-Organization-Environment (TOE)

Framework: The TOE framework (Tornatzky & Fleischer, 1990) [22] offers a robust lens for understanding firm-level technological innovation adoption. It proposes that three contexts influence this process: the Technological context (internal and external technologies), the Organisational context (firm size, structure, and management support), and the Environmental context (industry, competitors, and regulations). This framework is ideal for structuring the analysis of enablers and inhibitors of GenAI adoption within the diverse UK market.

Generative AI and Business Performance

Business performance is a multidimensional construct incorporating both financial (e.g., profitability, sales growth) and non-financial (e.g., market share, customer satisfaction) metrics (Richard *et al*., 2009) [21]. Prior research on related technologies like traditional AI and analytics has generally shown a positive, though often indirect, correlation with performance (e.g., Wamba-Taguimdje *et al*., 2020) [25]. GenAI's distinguishing feature is its generative nature, enabling it to perform tasks once exclusive to human professionals, such as drafting legal contracts, creating marketing campaigns, writing software code, and designing new products (Davenport & Ronanki, 2018) [7]. This can lead to direct performance impacts through new revenue streams (e.g., AI-as-a-Service) and unique value propositions. Therefore, the researcher formulates hypothesis one as follows:

H_1: Generative AI adoption is positively associated with business performance in the UK.

The Mediating Role of Operational Efficiency

Operational efficiency, defined as the ratio of outputs to inputs, is reflected in cost reduction, process speed, and error minimization (Wu *et al*., 2020) [27]. GenAI serves as a powerful automation tool that extends beyond routine tasks to cognitive automation. For instance, it can automate customer service via advanced chatbots, summarize extensive reports for management, streamline code development and testing in IT, and optimize logistics within supply chains (Brynjolfsson & McAfee, 2017) [4]. By performing these tasks faster, at a lower cost, and with greater consistency, GenAI frees human capital for higher-value activities, thereby boosting operational efficiency. This efficiency, in turn, translates into lower operational costs, higher profit margins, and improved competitive positioning on price and speed, ultimately enhancing business performance. Accordingly, the researcher proposes:

H_2: Operational efficiency mediates the relationship between generative AI adoption and business performance in the UK.

The Mediating Role of Product Innovation

Product innovation involves the introduction of new or significantly improved goods or services (OECD, 2018) [18]. GenAI acts as a catalyst for innovation, augmenting human creativity and accelerating the innovation cycle (Füller *et al*., 2022) [11]. It can generate a wide array of design prototypes, propose new product features through market data analysis, create personalized marketing content at scale, and even assist in developing new chemical compounds or materials (Korzynski *et al*., 2023) [15]. This reduces the time and cost of the ideation and development phases. Firms leveraging GenAI for innovation can launch more new products to market faster, capture first-mover advantages, and access new market niches, all of which positively impact performance (Nambisan *et al*., 2019) [17]. Hence, the researcher hypothesizes that:

H_3: Product innovation mediates the relationship between generative AI adoption and business performance in the UK.

Drivers and Barriers to GenAI Adoption: A TOE Perspective

Understanding the facilitators and inhibitors of adoption is critical. Using the TOE framework and existing IT adoption literature, the researcher identifies key factors relevant to the UK context.

1. Technological Context:

Technological Competence: A firm's existing IT infrastructure and AI capabilities form the foundation for adopting complex technologies like GenAI (Liang *et al.*, 2007; Oyakhire, 2020) [16, 19].

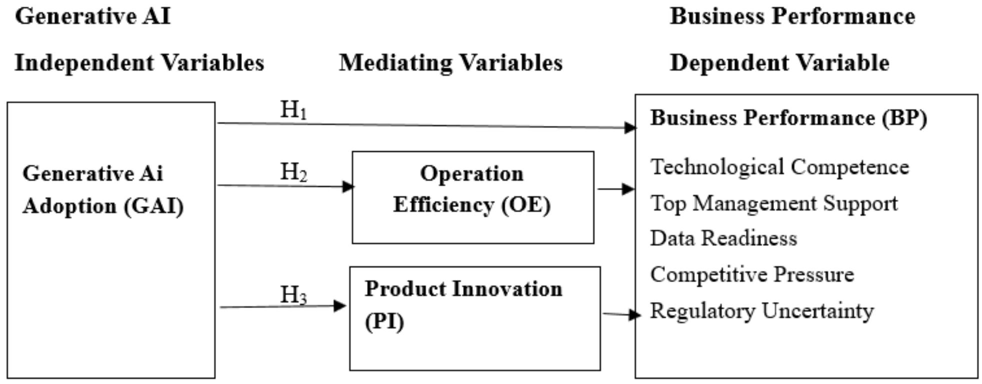
2. Organizational Context:
Top Management Support: Leadership understanding and endorsement of AI initiatives are crucial for resource allocation and managing organizational change (Chatterjee *et al.*, 2021) [5].

Data Readiness: The quality, availability, and governance of data are paramount, as GenAI models are inherently data-dependent (Ransbotham *et al.*, 2017) [20].

Environmental Context:
Competitive Pressure: The feeling that competitors are implementing (or are adopting) GenAI may inspire a strong motivation to also adopt it, as a way to keep pace (Wang *et al.*, 2010) [26].

Regulatory Uncertainty: The changing regulatory conditions of AI in the UK, inclusive of intellectual property, liability, and data protection challenges (i.e., GDPR), may give rise to perceived risks that hinder investment (Koch *et al.*, 2021) [14].

Conceptual Model
In accordance with the literature examined and the hypotheses stated, the following conceptual model (Figure 1) was constructed.



Source: Researcher's model, 2025

Fig 1: Conceptual Research Model

The conceptual model represents the direct and indirect effects of the adoption of the independent variable, Generative AI (GenAI), on business performance as mediated by the operational efficiency and product innovation variables. The model is based on the Technology-Organisation-Environment (TOE) framework, which is a set of drivers and obstacles that influence the adoption of GenAI.

Method
Research Design and Data Collection
This study utilized a cross-sectional survey design to gather quantitative data from organisations operating in the United Kingdom. The unit of analysis was the organisation, with the participants' sample being senior executives such as Chief Executive Officers (CEOs), Chief Technology Officers (CTOs), and heads of digital transformation, who possessed extensive knowledge of their firm's AI strategy and performance outcomes.
To ensure diversity, the sampling frame was constructed using the FAME database, targeting firms with 50 or more employees across a range of industries: technology, finance, manufacturing, retail, and professional services. A stratified random sampling approach was employed to guarantee proportional representation from both small- and medium-sized enterprises (SMEs, 50 - 249 employees) and large organizations (250, and above employees).
Data collection was conducted online via the Qualtrics platform between June and August 2024. The survey instrument was pre-tested with 7 academic and industry experts, followed by a pilot survey with 30 managers to refine questions and ensure face validity.
2,000 copies of the questionnaire were distributed, and 345 responses were received. After removing incomplete or inattentive submissions, a final sample of 312 usable responses was secured, yielding a response rate of 15.6%, which is consistent with surveys at this executive level (Cycyota & Harrison, 2006) [6]. A test for non-response bias comparing early and late respondents on key firmographic variables showed no significant differences (Armstrong & Overton, 1977) [1].

Measures
All constructs were operationalized using multi-item reflective scales adapted from established sources and modified for the GenAI context. Responses were captured on a five-point Likert scale (1="Strongly disagree" to 5="Strongly agree"), except for business performance, which used a relative comparison scale. The full measurement instrument is provided in Appendix A.

1. **Generative AI Adoption (GAI):** A 5-item tool based on Wang *et al.* (2010) [26] and Chatterjee *et al.* (2021) [5], which assesses the extent and complexity of GenAI use (e.g., use as automated content creation and product development).
2. **Operational Efficiency (OE):** A 5-item scale adapted from Wang *et al.* (2010) [26] and Chatterjee *et al.* (2021) [5] assessed the extent and sophistication of GenAI use.
3. **Operational Efficiency (OE):** A 4-item scale from Wu *et al.* (2020) [27] measured perceived improvements in cost, speed, and error reduction.
4. **Product Innovation (PI):** A 4-item scale based on Nambisan *et al.* (2019) [17] evaluated the firm's ability to launch new/improved products with GenAI assistance.
5. **Business Performance (BP):** A 6-item subjective scale

by Richard *et al*. (2009) [21] gauged performance relative to competitors on profitability, sales, market share, and customer satisfaction.

6. **TOE Drivers and Barriers:** Technological Competence (Liang *et al*., 2007) [16], Top Management Support (Chatterjee *et al*., 2021) [5], Data Readiness (Ransbotham *et al*., 2017) [20], Competitive Pressure (Wang *et al*., 2010) [26], and Regulatory Uncertainty (Koch *et al*., 2021) [14] were included as constructs.

The control variables included firm size (log of number of employees), firm age (years since inception), and industry type (dummy coded).

Data Analysis
Data analysis was performed in SmartPLS 4.0 using a two-step approach: first assessing the measurement model's reliability and validity, then evaluating the structural model to test hypotheses (Hair *et al*., 2019) [12]. PLS-SEM was selected for its suitability for complex models with mediators and its ability to handle non-normal data distributions, making it ideal for exploratory research on emergent technologies like GenAI.

Results
Sample Profile
The final sample (N=312) comprised 42% small/medium-sized enterprises (SMEs) and 58% large enterprises. The industry distribution was: Technology (28%), Financial Services (22%), Manufacturing (18%), Retail (12%), Professional Services (11%), and Other (9%). The respondents' roles included CEO/MD (25%), CTO/CIO (30%), COO (15%), and other senior management (30%).

Measurement Model Assessment
Evaluation of the measurement models supported validity and reliability. Table 1 indicates that Cronbach's alpha and composite reliability (CR) were above 0.70, and that all indicators were above 0.70, and the average variance extracted (AVE) was above 0.50, which shows good convergent validity (Fornell & Larcker, 1981; Hair *et al*., 2019) [10, 12].

Table 1: Reliability and Convergent Validity of Constructs

Construct	Items	Loadings Range	Cronbach's Alpha	Composite Reliability	AVE
GenAI Adoption (GAI)	5	0.78 - 0.89	0.88	0.91	0.68
Operational Efficiency (OE)	4	0.82 - 0.88	0.89	0.92	0.75
Product Innovation (PI)	4	0.85 - 0.91	0.91	0.94	0.79
Business Performance (BP)	6	0.76 - 0.87	0.92	0.94	0.71
Technological Competence	3	0.83 - 0.90	0.87	0.92	0.79
Top Management Support	3	0.88 - 0.92	0.91	0.94	0.85
Data Readiness	3	0.81 - 0.87	0.85	0.91	0.76
Competitive Pressure	3	0.79 - 0.86	0.83	0.90	0.75
Regulatory Uncertainty	3	0.84 - 0.89	0.86	0.92	0.78

Source: Researcher's field work, 2025

The discriminant validity was tested using the Fornell-Larcker criterion (Table 2) and the heterotrait-monotrait (HTMT) ratio of correlations. The square root of the average variance extracted (AVE) of each construct (diagonal elements in Table 2) was larger than the maximum correlation between that construct and any other construct. Additionally, all HTMT estimates were lower than the conservative level of 0.85 (Henseler *et al*., 2015) [13], hence validating the existence of discriminant validity.

Table 2: Fornell-Larcker Criterion for Discriminant Validity

Construct	1	2	3	4	5	6	7	8	9
1. GAI	0.82								
2. OE	0.58	0.87							
3. PI	0.62	0.51	0.89						
4. BP	0.55	0.49	0.61	0.84					
5. TechComp	0.67	0.41	0.48	0.39	0.89				
6. TopMgmt	0.71	0.45	0.52	0.42	0.59	0.92			
7. DataRead	0.59	0.38	0.44	0.35	0.63	0.51	0.87		
8. CompPress	0.48	0.31	0.39	0.33	0.29	0.41	0.27	0.87	
9. RegUncert	-0.41	-0.25	-0.32	-0.28	-0.35	-0.39	-0.31	-0.18	0.88

Source: Researcher's field work, 2025 / Note. Diagonal elements (in bold) are the square root of the AVE.

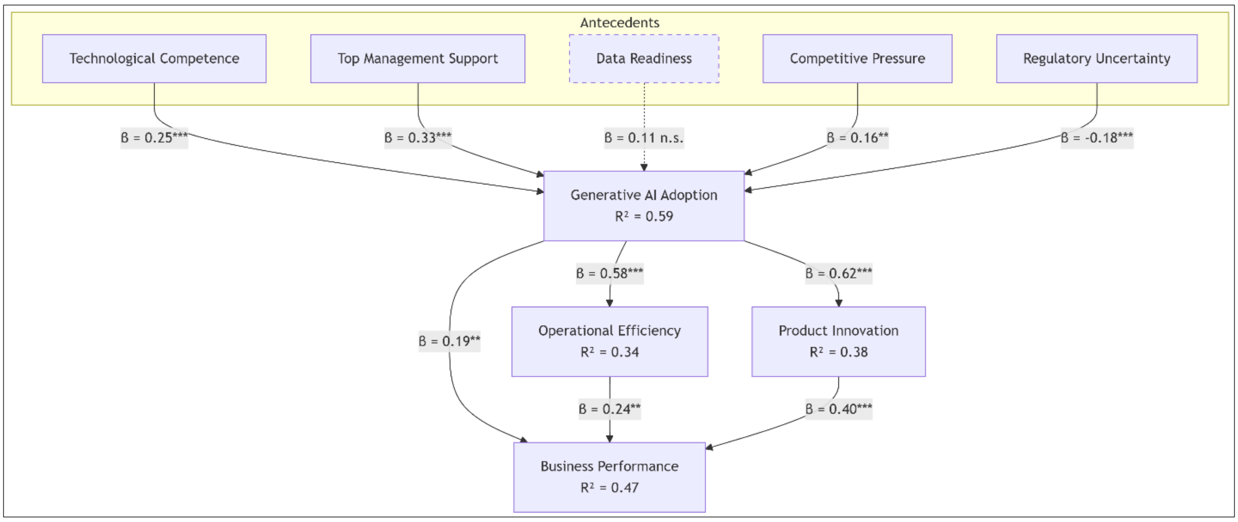
Structural Model and Hypothesis Testing
The structural model was assessed for collinearity, path coefficients (β), coefficient of determination (R^2), and predictive relevance (Q^2). The Variance Inflation Factor (VIF) values for all predictor constructs were below 3, indicating no critical collinearity issues (Hair *et al*., 2019) [12]. The model's explanatory power was substantial, with R^2 values of 0.59 for GenAI Adoption, 0.34 for Operational Efficiency, 0.38 for Product Innovation, and 0.47 for Business Performance.

Hypotheses were tested using a bootstrapping procedure with 5,000 subsamples. The results are presented in Table 3 and Figure 2.

Table 3: Hypothesis Testing Results

Hypothesis	Path	B	t-value	p-value	Supported?
H1	GAI -> BP	0.19	3.45	0.001	Yes
H2	GAI -> OE -> BP	0.14	3.12	0.002	Yes
H3	GAI -> PI -> BP	0.25	5.78	0.000	Yes
-	TechComp -> GAI	0.25	4.89	0.000	-
-	TopMgmt -> GAI	0.33	6.45	0.000	-
-	DataRead -> GAI	0.11	1.92	0.055	(Marginal)
-	CompPress -> GAI	0.16	3.21	0.001	-
-	RegUncert -> GAI	-0.18	3.67	0.000	-

Source: Researcher's field work, 2025 /
Note: β = Standardized path coefficient.



Source: Researcher's field work, 2025
Note: *p < 0.05, ** p < 0.01, *** p < 0.001; n.s. = not significant.

Fig 2: Structural Model Results with Path Coefficients (β) and R^2 values

The analysis provides empirical support that is substantial in terms of Hypothesis 1 since the adoption of Generative AI (GenAI) has a statistically significant positive effect on business performance ($\beta = 0.19$, $p < 0.01$). Both mediation hypotheses were also confirmed. The indirect relationship through Operational Efficiency (GAI -> OE -> BP, $\beta = 0.14$, $p < 0.01$) supports H2, but the relationship through Product Innovation (GAI -> PI -> BP, $\beta = 0.25$, $p < 0.001$) supports H3. The mediating effect is stronger with the innovation pathway. When all the direct and indirect effects are summed up, the overall effect of GenAI adoption on performance is 0.58, which is quite significant, and it should not be underestimated.

In terms of determinants of adoption, Technological Competence ($\beta = 0.25$, $p < 0.001$), Top Management Support ($\beta = 0.33$, $p < 0.001$), and Competitive Pressure ($\beta = 0.16$, $p < 0.01$) were strong, significant drivers. Regulatory Uncertainty was a significant barrier ($\beta = -0.18$, $p < 0.001$). Data Readiness showed a marginally significant positive effect ($\beta = 0.11$, $p = 0.055$). The control variables (firm size, age, industry) showed no significant effects on the main relationships.

The predictive validity was established, and the values of Stone-Geisser Q2 were greater than zero in all endogenous constructs (BP = 0.32; OE = 0.25; PI = 0.29; GAI = 0.41), which supported the relevance of the model.

Discussion

This study set out to empirically investigate the relationship between generative AI adoption and business performance in the UK. The findings provide robust evidence that GenAI is a substantive driver of business success.

Findings and Theoretical Implications

The confirmation of H1 establishes a positive link between GenAI adoption and business performance. The finding aligns with the core views of the Resource-Based View. GenAI seems to enhance the competitive advantage and financial success of a company by enhancing its core competencies (Barney, 1991; Brynjolfsson & McAfee, 2017) [2, 4].

The mediating effects explained in H2 and H3 provide additional explanations for the mechanisms that support these benefits. Operation efficiency and product innovation are both relevant channels of connection between GenAI and improved performance. This dual-pathway model enriches the literature by moving beyond a simple input-output model and explicating the internal capabilities through which GenAI creates value. The finding that the mediating effect of product innovation ($\beta = 0.25$) is stronger than that of operational efficiency ($\beta = 0.14$) is particularly insightful. It suggests that for UK firms, the primary value of GenAI may lie less in costcutting and more in its capacity to drive growth and differentiation. This underscores the "generative" aspect of the technology, its ability to create novel outputs that fuel innovation, as its most potent economic characteristic (Nambisan *et al*., 2019; Füller *et al*., 2022) [17, 11].

Adoption drivers that are identified by the Technology-Organisation-Environment (TOE) framework show that the most influential factor is leadership endorsement. Top Management Support (β=0.33) emphasises the fact that the successful AI implementation is strongly dependent on strategic vision and managerial commitment (Chatterjee *et al*., 2021) [5]. Equally, Technological Competence highlights the need for an underlying digital infrastructure and competent staff. At the same time, Competitive Pressure demonstrates that companies are beginning to view the use of GenAI as a strategic requirement and not a luxury innovation. On the other hand, Regulatory Uncertainty is a relevant deterrent that reflects the current discussions in the UK and EU on the subject of AI ethics, accountability, and compliance (Koch *et al*., 2021) [14]. The marginally significant effect of Data Readiness ($p = 0.055$) suggests that while data is important, firms may be finding ways to work with existing data or use external datasets, though it remains a potential challenge.

Practical and Policy Implications

For business leaders, these results validate strategic investment in GenAI, highlighting its role as an engine for innovation and customer-centric change, not just automation. Cultivating an innovation-focused culture, developing digital literacy, and fostering human-AI collaboration are critical.

To policymakers, the findings support the need to continue support for the National AI Strategy in the UK. Three policy priorities emerge:

1. **Clarifying the Regulatory Framework:** Providing predictable, clear, and innovation-friendly regulations that will reduce uncertainty and encourage investment in the United Kingdom.
2. **Boosting Technological Competence:** Supporting skills development programmes, especially for SMEs, and promoting access to AI compute infrastructure and tools in some designated centres.
3. **Fostering Collaboration:** Encouraging more partnerships between industry and academia to accelerate research and development, and address sector-specific challenges.

Limitations and Future Research

This study has limitations that present avenues for future research. The cross-sectional design establishes association, not causality; longitudinal studies are needed. Self-reported data, though validated, could be supplemented with objective financial metrics. The UK-specific context invites comparative cross-regional studies. Future research could explore industry-specific dynamics, implementation strategies, and the ethical and workforce implications of GenAI integration.

Conclusion

It is one of the first empirical studies of the use of Generative AI and business performance in the United Kingdom. The findings are that GenAI has a positive impact on the success of firms, and it works in two ways: improving operational performance and, more fundamentally, prompting product innovation. For UK organizations, GenAI represents not merely a tool for incremental improvement but a strategic driver of transformation and growth. Realizing this potential requires leadership vision, technological readiness, and policy frameworks that thoughtfully balance innovation with ethical governance.

Research Funding

This research was solely funded by the researcher, without external funding.

Appendices

Appendix A: Measurement Items

All items were measured on a 5-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree), unless otherwise stated.

Generative AI Adoption (GAI)

1. Our company uses generative AI technologies in our core business processes.
2. We use generative AI for automating content creation (e.g., text, images, video).
3. We use generative AI to support product development and innovation activities.
4. Generative AI is integrated into our customer-facing applications and services.
5. Senior management actively advocates for the use of generative AI in our firm.

Operational Efficiency (OE)

1. The adoption of generative AI has helped us reduce our operational costs.
2. Generative AI has significantly improved the speed of our internal processes.
3. Generative AI has enabled us to minimize errors in our operational tasks.
4. Overall, our operational efficiency has improved due to generative AI.

Product Innovation (PI)

1. We frequently introduce new products/services developed with the help of generative AI.
2. Generative AI has enhanced our ability to create innovative features for our products/services.
3. The use of generative AI has shortened our new product development cycle.
4. Compared to our competitors, our new products/services are more innovative due to our use of generative AI.

Business Performance (BP)

(Relative to your main competitors over the last 12 months, how would you rate your firm's performance on the following dimensions? 1 = Much Worse, 7 = Much Better)

1. Profitability
2. Sales Growth
3. Market Share
4. Return on Investment (ROI)
5. Customer Satisfaction
6. Overall Competitive Position

Technological Competence

1. Our firm has the necessary technical infrastructure to support generative AI.
2. We have employees with the skills needed to implement

and use generative AI.
3. Our IT department is capable of supporting generative AI projects.

Top Management Support
1. Top management believes that investing in generative AI is critical for our future.
2. Top management provides the necessary resources for generative AI initiatives.
3. Top management is actively involved in the rollout of generative AI in our firm.

Data Readiness
1. Our firm has high-quality data that is suitable for training generative AI models.
2. Our data is easily accessible for AI projects.
3. We have strong data governance policies in place.

Competitive Pressure
1. Our main competitors are actively using generative AI.
2. We feel significant pressure from our competitors to adopt generative AI.
3. Not adopting generative AI would put our firm at a competitive disadvantage.

Regulatory Uncertainty
1. We are concerned about the legal and regulatory risks associated with generative AI (e.g., copyright, liability).
2. The lack of clear regulations for AI in the UK hinders our investment in generative AI.
3. We are uncertain about how data protection laws (like GDPR) apply to our use of generative AI.

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