More than just Plug and Play: Early Evidence on Organizational Capital and AI Adoption*

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Abstract

This paper provides early evidence that AI adoption by firms is linked to management practices in unique ways. Using panel data from the UK Management and Expectations Survey (MES), we find that firms with higher baseline management scores are significantly more likely to adopt AI. This relationship is specific to AI: the same management practices show no relationship with the adoption of robotics, specialized equipment, or specialized software. We also find that management capabilities related to measurement are most strongly related to AI adoption. These results suggest that the relevant organizational complementarities differ for different technologies with implications for shaping policies to encourage AI adoption by firms.

JEL-Classification: D22, O33, M11, O31, L23.

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1 Introduction

Artificial intelligence holds great promise for productivity and GDP growth (McKinsey & Company, 2023), but adoption in business remains surprisingly uneven (Calvino et al., 2026), with large firms being 10 percentage points more likely to adopt AI than smaller firms (Office for National Statistics, 2025). This gap has remained even as large language models (LLMs) have become more user-friendly, and their cost continues to fall (Demirer et al., 2025; Arsenovic and Casado, 2024; Epoch AI, 2024; Huynh, 2024; Ng, 2024). Understanding what separates early adopters from laggards has become a central question for economists and policymakers.

One leading explanation emphasizes organizational capabilities. Building on the seminal works of Bresnahan et al. (2002) and Brynjolfsson and Hitt (2000, 2003), a substantial literature argues that new technologies require complementary investments in organizational practices to generate value. However, the evidence on which organizational capabilities[1] matter for which technologies remains limited. It is an open question whether AI differs from other technologies such as prior generations of digital in the specific requirements involved.

This paper provides the first evidence that management practices predict AI adoption in unique ways. Using panel data from the UK Management and Expectations Survey (MES), we find that firms with higher baseline management scores are significantly more likely to adopt AI. This relationship is specific to AI: the same management practices that strongly predict AI adoption show no relationship with the adoption of robotics, specialized equipment, or specialized software. Management quality also predicts cloud computing adoption, though the effect is smaller, consistent with both technologies (AI and cloud computing) requiring ongoing organizational change. While these results may partly reflect AI's status as an emerging technology at the time of our study, they provide important insights into the organizational capabilities that enable firms to successfully adopt novel technologies in their early diffusion phase.

[1]We acknowledge that organizational capital, management practices, and management capabilities represent distinct concepts in different contexts. Organizational capital being broader and more latent, while management practices refer to specific, observable activities. However, for the purposes of this paper, we use these terms interchangeably when referring to the structured management activities measured in our survey, following the convention in the empirical management literature (Bloom and Van Reenen, 2007; Bloom et al., 2012, 2019).

We also find that among the four components of management practices, monitoring capabilities are the strongest predictors of AI adoption. Practices related to continuous improvement or employee relations show weaker or insignificant effects. These results have important theoretical implications. They suggest that the relevant organizational complementarities differ for different technologies. Unlike industrial robots or manufacturing equipment, it is reasonable to hypothesize that AI systems will affect co-ordination and monitoring, and require adjustment within the business processes. They produce outputs that need to be integrated into decision-making processes, and refined through iterative feedback. This organizational work is precisely what structured management practices enable.

Moreover, we find among firms that operate across multiple sites in the UK, those with decentralized product development are significantly more likely to adopt AI, even controlling for management quality. This hints that AI adoption may benefit from a decentralized decision-making structure for product development. Unlike robotics or specialized equipment, where investment decisions can readily be made centrally based on clear financial criteria, AI applications are more likely to be context-specific and require domain or technical knowledge to identify valuable use cases. We hypothesize that teams working directly with business processes are better positioned to recognize where AI can add value, and that this pattern distinguishes AI from technologies that can be mandated from the top down.

Our empirical design addresses key identification challenges in the technology adoption literature. By measuring management practices in 2020 and AI adoption in 2023, we establish temporal precedence, so partly mitigating concerns about reverse causality. The specificity of our results to AI rather than other technologies provides a powerful check against the concern that we are simply capturing general firm quality or unobserved correlates of both management and technology adoption. For if well-managed firms were just better at everything, we would expect management quality to predict the adoption of all technologies to a similar extent.

Several additional findings support this interpretation. First, the relationship between management and AI adoption persists even when we control for concurrent adoption of information and communication technologies (ICT) and other technologies, including cloud computing, robotics, specialized software and specialized equipment. This rules out the possibility that management metrics simply capture a firm's general propensity to invest

in technology. Second, we find similar patterns when examining short-term adoption intentions: among firms that have not yet adopted AI, management quality in 2020 predicts plans to adopt in 2024. This suggests that management shapes not just the implementation decision but also strategic thinking about AI. Third, our data shows[2] that AI adopters invest substantially more in complementary intangible assets and experience faster subsequent productivity and employment growth. AI-users spent six times more than non-users on advertising and marketing services, and four times more on computer softwares and databases. These patterns are consistent with management practices enabling firms to extract value from AI through complementary investments.

This paper makes five main contributions. We provide the first direct evidence on particular management practices as predictors of AI adoption using representative firm-level data with a panel structure. While cross-sectional correlations between management and technology adoption are well documented (Bloom et al., 2012; McElheran et al., 2025), the direction of causality has remained unclear. Our temporal design establishes that management quality positively predicts subsequent adoption. Moreover, most firm-level evidence relies on indirect proxies to measure AI adoption: patents (Miric et al., 2023; Webb, 2019; Datadog, 2024), workforce composition (Acemoglu et al., 2022b; Alekseeva et al., 2021; Goldfarb et al., 2023), task characteristics (Eloundou et al., 2023; Felten et al., 2021), and machine learning usage (Siedschlag and Duran Vanegas, 2025). Our data uniquely provides direct identification of AI-adopting firms through self-reported responses. While earlier US studies similarly employed self-reported data (McElheran et al., 2024; Acemoglu et al., 2022a), their data predate the AI boom triggered by ChatGPT's release in late 2022, when both the adoption landscape and public understanding of AI capabilities were fundamentally different.

Second, we demonstrate that organizational complementarities are technology-specific. The Bresnahan et al. (2002) framework emphasizes that information technology investments require complementary organizational changes to generate productivity gains, but this literature has largely treated "IT" as a monolithic category. We show that different technologies make different organizational demands. AI adoption requires structured monitoring capabilities in ways that specialized softwares do not. This specificity has important implications for modelling technology adoption and productivity impacts.

[2] see table A.2

Third, we identify the type of management practices in the survey data that enable AI adoption. It is specifically monitoring practices, such as use of KPIs and target-tracking, along with decentralized product development, that predict adoption. This suggests that organizations seeking to adopt AI (for productivity gains, product or process innovation) should focus on developing structured performance measurement or information systems and empowering technical teams. Our results suggest this might be more effective than than focusing on management practices broadly or mandating AI adoption from the top down.

Fourth, this paper contributes timely evidence on AI adoption patterns in the post-LLM era. While prior research has examined firm-level AI adoption (Acemoglu et al., 2022a; McElheran et al., 2024; Lo Turco, 2026; Calvino and Fontanelli, 2026), these studies employ data collected before 2022. As such, they do not capture the transformational shift in AI accessibility following the release of ChatGPT and other large language models. Our 2023-2024 data provide insight into adoption behavior during this inflection point in AI diffusion.

Lastly, our findings speak directly to the policy debates about accelerating AI diffusion. If capital constraints were the primary barrier to AI adoption, subsidies or tax incentives for AI investments would be the appropriate policy response. But if organizational capabilities are also the binding constraint, then policies must address management quality and organizational readiness. Our findings suggest that different technologies will require different types of support.

2 Literature and Theoretical Motivation

Foundational research in both management and economics literature on technology adoption has identified the factors that determine whether firms successfully implement new technologies, with the role of organizational capital in general a clear theme.

Corrado et al. (2009) provides a now-standard framework for the comprehensive measurement and accounting of intangibles. Within this broad class of assets, organizational capital has emerged as a particularly important determinant of ICT adoption. Bloom and Van Reenen (2007) developed structured measures of management practices, a proxy for organizational capital.

The seminal work by Brynjolfsson and Hitt (2000, 2003) found that productivity gains

from ICT adoption only materialize when these investments are accompanied by complementary organizational changes, such as the restructuring of work processes and management practices. Bresnahan et al. (2002) formalized this insight, demonstrating that information technology, organizational capital, and worker skills form a "triple helix" of complementarities. Firms achieved productivity gains only through coordinated investment across all three dimensions. Bloom et al. (2012) confirmed these patterns using firm-level data, demonstrating that well-managed firms are both more likely to adopt ICT and achieve higher productivity growth.

Subsequent empirical work has confirmed the importance of good management for ICT adoption across diverse contexts. Yang et al. (2015) found that Software as a Service (SaaS) adoption depends on a combination of technological, organizational, and environmental readiness within firms. Meanwhile, Oliveira et al. (2014) and Clohessy et al. (2018) demonstrated that existing technological and organizational capabilities determine adoption patterns by reducing integration costs, addressing governance challenges, and managing regulatory requirements. In terms of mechanisms, the literature finds that decentralization facilitates adoption (Bresnahan et al., 2002), top management support drives implementation success (Faiz et al., 2024), and organizational slack enables innovation (Zhor, 2018).

In the management and information systems literature, foundational works such as Rogers's (2003) Diffusion of Innovations theory emphasized innovation characteristics (relative advantage, compatibility, complexity), adopter characteristics, and communication channels, while the Technology-Organization-Environment framework (Tornatzky et al., 1990) highlights the technological context, organizational context, and environmental pressures as key determinants. Empirical work has validated these frameworks. Firm size, managerial structure, employee expertise, competitive pressure, and technological infrastructure consistently predicted adoption across diverse technologies and contexts (see reviews by Oliveira and Martins, 2011; Faiz et al., 2024). We provide a short summary of determinants of ICT adoption in table 1.

Academic work on ICT adoption finds that various forms of *intangible capital* are necessary complementary investments. Studies consistently find that firms with R&D capacity exhibit higher rates of ICT adoption (Gómez and Vargas, 2012; Giunta and Trivieri, 2007). Firms with stronger innovation capabilities more readily integrate new technologies into their operations. Previous studies also find that firms with higher skill

Table 1: Determinants of ICT technology adoption

Category	Factors	Articles	AI-specific
Technological factors	Technology infrastructure and resources	Horani et al. (2025); McElheran et al. (2024); McElheran et al. (2025)	Yes
		Oliveira et al. (2014)	No
	R&D	Gómez and Vargas (2012); Giunta and Trivieri (2007)	No
	Employee expertise	Agarwal (2022)	Yes
		Svahn et al. (2017); Oliveira et al. (2014); Garrison et al. (2015)	No
Organisational factors	Firm size	McElheran et al. (2024); Acemoglu et al. (2022a)	Yes
		Clohessy et al. (2018); Oliveira et al. (2014); Gómez and Vargas (2012); Wang et al. (2010); Hannan and McDowell (1984); Giunta and Trivieri (2007)	No
	Decentralization	Agrawal et al. (2024); Coyle et al. (2025)	Yes
		Bresnahan et al. (2002)	No
	Top management support	Chatterjee et al. (2021); Chen et al. (2021); Horani et al. (2025)	Yes
		Yang et al. (2015); Clohessy et al. (2018); Oliveira et al. (2014); Faiz et al. (2024); Srivastava et al. (2022)	No
	Management practices and quality	Phuoc (2022); McElheran et al. (2025)	Yes
		Brynjolfsson and Hitt (2000, 2003), Bloom et al. (2012), Giunta and Trivieri (2007); Srivastava et al. (2022); Garrison et al. (2015), Brynjolfsson et al. (2021);	No
Others	External pressure	Coyle et al. (2025); Horani et al. (2025)	Yes
		Yang et al. (2015); Faiz et al. (2024)	No
	Business and vendor partnership	Arroyabe et al. (2024); Chen et al. (2021); Horani et al. (2025)	Yes
		Giunta and Trivieri (2007)	No

levels adopt ICT technologies faster (Svahn et al., 2017; Oliveira et al., 2014; Garrison et al., 2015; Byrd and Turner, 2001). Overall, the literature emphasizes intangible assets as key complements to ICT adoption, with existing technological infrastructure playing a facilitating role by lowering implementation and compatibility constraints (Svahn et al., 2017).

In the context of AI, recent academic works describe how adoption is also shaped by technological, organizational, and environmental contexts.

Recent evidence documents substantial variation in AI adoption across firms and countries. Calvino et al. (2026) show that digital technology diffusion patterns in the age of AI differ significantly from previous technological waves, with adoption concentrated among larger, more productive firms. Similarly, Yotzov et al. (2026) finds widespread but shallow AI adoption across firms.

Consistent with the ICT adoption literature, digital infrastructure, organizational capital, and skills are consistently identified as critical drivers of AI adoption (Agarwal, 2022; Horani et al., 2025; Phuoc, 2022). Moreover, the literature documents that firm size, organizational structure, and managerial capabilities predict adoption patterns (Acemoglu et al., 2022a; McElheran et al., 2024; Agrawal et al., 2024; Chen et al., 2021; Horani et al., 2025; McElheran et al., 2025).

Interestingly, some characteristics of AI suggest a priori that the technology *may* require more ogranizational capital than other ICTs. It demands continuous learning and supervision rather than one-time implementation (Agrawal et al., 2019). Value extraction explicitly requires greater coordination capabilities (Agrawal et al., 2024; McElheran et al., 2024). Adoption is also associated with greater uncertainty about suitable applications and organizational fit. As such, capability for experimentation and refinement is critical for effective implementation (Cockburn et al., 2018). Moreover, McElheran et al. (2025) highlights that, as a general-purpose technology, AI also requires substantial complementary investments in intangible capital, such as better management practices. They argue that productivity gains from these technologies take a long time to materialize because of the organizational restructuring required to generate value for firms. These imply that AI adoption may place greater demands on management capabilities than other ICTs. But whether AI's organizational requirements are quantitatively distinct from other technologies, or simply extend established ICT adoption patterns remains an open empirical question.

3 Data

The main dataset that we employ for our empirical analysis is the UK's Management and Expectations Survey (MES), developed by the Office for National Statistics (ONS) in partnership with the Economic Statistics Centre of Excellence (ESCoE). The survey provides comprehensive firm-level data on firm characteristics, management practices and business expectations in Great Britain and Northern Ireland (included in the 2023 sample only). The UK's MES data is comparable to data collected in the US's Management and Organizational Practices Survey (USMOPS) and the German Management and Organizational Practices Survey (GMOPS).

The MES is conducted every three-years (2017, 2020, 2023). We use data from the 2020 and 2023 survey waves for our analysis. The 2023 MES sampled more than 53,000 businesses in the UK between December 2023 and March 2024. It achieved a response rate of 26.9% - three percentage points higher than the 2020 wave (Office for National Statistics, 2024). The sample excludes micro-businesses (fewer than 10 employees) and those in agriculture, financial services and the public sector.

We match the 2023 MES wave with the 2020 wave.[3] Removing firms that did not respond to the question on technology use leaves us with 7,525 valid respondents. Partial responses to the survey further restrict our sample for the baseline regression to 1,292 respondents. We provide a summary of the data in table 2.

3.1 Adoption of AI and other technologies

The 2023 MES questionnaire[4] included a section that focused on the use of five different technologies: AI, cloud computing, robotics, specialized software, and specialized equipment.

Respondents were asked whether the business had used each of these technologies in the reference year of 2023. A firm could respond that the technology is not applicable to its business; the technology is applicable but has not been tested or used; the technology has

[3]Since businesses in Northern Ireland are only included in the 2023 sample, our final dataset of observations is restricted to firms in Great Britain

[4]This is the first instance where question on technology adoption was included in an ONS survey. Subsequent to this survey, the Business Insights and Conditions Survey also included questions on technology adoption.

Table 2: Variable Definitions and Data Sources

Variable	Definition
Panel A: Management and Expectations Survey (MES)	
AI Adoption	Binary indicator equal to 1 if firm uses AI as part of processes or methods in 2023, 0 otherwise
Management Score	Overall management quality score (0-1), computed as average across all management practice items; higher values indicate better management
Ln Labor Productivity 2020	Natural logarithm of turnover per employee in 2020
Family Management	Binary indicator equal to 1 if firm is family-managed in 2020
Foreign Ownership	Binary indicator equal to 1 if firm is foreign-owned in 2020
Panel B: Annual Business Survey (ABS)	
R&D	Binary indicator equal to 1 if firm conducts in-house R&D or plans to do so
Log Brand	Natural logarithm of expenditure on advertising and marketing services (£); not available for financial sector (SIC K)
Total Software	Total expenditure on computer software and databases, either developed in-house or purchased externally (£,000)
Panel C: Fixed Effects	
Size FE	Five employment bands: 10-19; 20-49; 50-99; 100-249; 250+ employees
Age FE	Four age bands: 0-5 years; 6-15 years; 16-25 years; 25+ years
Industry FE	Eight broad SIC 2007 categories: non-manufacturing production; manufacturing; construction; distribution, hotels & restaurants; transport, storage & communication; business services; real estate; other services
Region FE	Twelve UK regions: North East; North West; Yorkshire & Humberside; East Midlands; West Midlands; East; London; South East; South West; Wales; Scotland; Northern Ireland

Notes: All control variables except growth measures (Δ Log Turnover, Δ Employment) are measured in 2020 to mitigate reverse causality concerns. Management sub-component scores are described in section 3.2.

been or is currently being tested but not used; the technology is used as part of processes or methods; or the responder does not know.

We construct a ***binary indicator of AI adoption*** that equals 1 if a firm uses AI as part of processes or methods in 2023, and equals 0 if the technology is applicable but has not been implemented. This approach excludes firms for whom AI is "not applicable", "tested but not using as part of the process" and those who responded "don't know," restricting our analysis to firms where non-adoption reflects organizational choices rather than business model constraints. This ensures we measure genuine adoption decisions among firms for which the technology is potentially relevant, rather than including mechanical zeros from firms where AI has no business application.[5] The average unweighted adoption rate of AI is 9% among UK businesses in 2023.

Respondents were also ask to indicate whether they plan to adopt any of the five specified technologies in 2024. The ***binary indicator of plan to adopt*** is set to 1 if the respondent selected AI in this question. Because the question specifically references the 2024 calendar year, interpretation of our results can only reflect on the immediate or near-future intention to adopt.[6]

One measurement consideration is that respondents' interpretations of AI may vary despite standardized survey definitions. The MES defines AI as '*technology where computer programs or machines can learn from data and perform tasks usually done by humans*' and provides concrete examples including conversational chatbots. While we cannot verify individual understanding, this definitional guidance likely reduces heterogeneity in interpretation relative to surveys without such clarification. Moreover, any resulting measurement error would likely attenuate coefficient estimates, biasing our tests against finding significant effects. This makes any of our positive findings conservative estimates. We show the frequency distribution of firms for each technology in table 3.

To enable cross-technology comparisons, we construct comparable ***adoption indicators for cloud computing, robotics, specialized software, and specialized equipment*** using the same procedures.

[5]Appendix A presents robustness checks examining alternative specifications across all technologies—comparing users to non-users (including 'not applicable'), users and testers to non-users, and users to testers only—confirming that our baseline specification appropriately captures adoption barriers rather than testing behavior or technological irrelevance.

[6]The 2023 MES collected responses between December 2023 and March 2024.

Table 3: Frequency Distribution of Technology Use (Merged 2020-2023 Sample)

	AI	Cloud Computing	Robotics	S. Software	S. Machinery
Not applicable to business	3,765	631	4,887	1,020	2,424
Applicable, not tested/used	1,393	444	948	403	450
Tested but not used	695	397	191	328	280
Used in processes/methods	646	5,652	640	5,268	3,564
Don't know	1,026	401	859	506	807
No response	18,838	18,838	18,838	18,838	18,838
Total	26,363	26,363	26,363	26,363	26,363

Notes: This table shows the frequency distribution of responses to technology adoption questions in the merged 2020-2023 MES panel sample. AI = Artificial Intelligence; S. Software = Specialized Software; S. Machinery = Specialized Machinery. "Not applicable to business" and "Don't know" responses are excluded from our main analysis to ensure we estimate adoption decisions among firms for whom each technology is potentially relevant. "No response" includes sampled firms that did not respond to the MES survey, gave only partial responses or did not answer the technology question.

3.2 Measuring management practices and organizational structure

Our main explanatory variable is the management score in 2020, which measures management quality in four different dimensions: continuous improvement; the use of key performance indicators (KPIs); the use of targets; and employment practices.[7]

The ***overall management score*** is the average of 16 categorical questions (21 survey items) and ranges between 0 and 1.[8]

A management score closer to 1 indicates the responding firm continuously reviews their processes for improvement, conducts regular performance reviews, trains workers and employs based on merit (Office for National Statistics, 2023). We also examine ***subcompo-***

[7] *Continuous improvement* captures whether firms respond to problems reactively or through structured, forward-looking processes. *Key performance indicators (KPIs)* assess how many metrics are tracked and how often they are reviewed by both managers and staff. *Targets* measure how performance goals are set, communicated, and linked to incentives. *Employment practices* evaluate promotion criteria, training levels, and how underperformance is addressed.

[8] We calculate the 2020 overall management score slightly differently from the ONS on the ground of further information needed. Our calculation excludes two survey items (questions 11b and 14b) from the overall 2020 management score and their corresponding components (Targets and Employment Practices). All regressions have been run with the original scores according to the ONS calculation to ensure consistency in results.

nent scores for each management dimension (computed as item averages, ranging 0-1 with higher values indicating better practices) to identify which specific capabilities drive AI adoption. This approach to measuring management practices is consistent with established practices in measuring organizational capital (Bloom and Van Reenen, 2007; Bloom et al., 2019). Previous studies reveal that management scores and their sub-components are positively correlated with productivity, profitability, and innovation in firms Bloom and Van Reenen (2007); Bloom et al. (2019, 2012); Vyas (2018).

Additionally, we explore the role of ***organizational structures*** in AI adoption. This is proxied as four binary variables: multiple-site operation; centralized hiring decision; centralized product development; and centralized investment decision. The multiple site operation variable is set to 1 if a respondent operates across multiple sites in the UK. Only when the respondent indicates that they operate across multiple sites do they have to answer subsequent questions about hiring, product development, and investment decisions. Centralized employment and product development equal 1 if the decisions to hire or to introduce new products and services are made only at the headquarters; they are set to 0 if these decisions are made at individual sites. Investment decisions are considered to be centralized (set to 1) if a business site needs prior authorization from their headquarters for any capital asset purchase over £1,000.

Because only businesses with multiple sites respond to questions about centralization of employment decisions, product development, and investment decisions, our results might only reflect the explanatory power of these variables among larger businesses in certain sectors.

3.3 Other variables

To isolate the relationship between organizational capital and AI adoption, we include several firm-level controls and fixed effects, with variable definitions provided in Table 2. Controls are measured in 2020 to mitigate reverse causality concerns, reflecting firm characteristics prior to the widespread diffusion of generative AI following ChatGPT's public release in November 2022. We control for labor productivity and ownership structure (family management and foreign ownership). Fixed effects account for firm size (five employment bands), age (four categories), industry (eight broad SIC groups), and region (twelve UK areas).

3.4 Annual Business Survey and intangible capital

To control for other intangible capital investments in UK businesses' decision to adopt AI, we link the panel MES 2020-2023 sample with two waves of the Annual Business Survey (ABS) in 2021 and 2022 separately. The ABS, conducted annually by the ONS, provides extensive firm-level financial data on UK businesses including turnover, wages and salaries, capital expenditure, and purchases of goods and services. Our analysis includes two sets of model specifications: with ABS 2021 variables and with ABS 2022 variables. For each following ABS variable, the coding is the same for 2021 and 2022.

R&D is a binary variable that equals 1 if the responding business conducts any in-house Research and Development for the reporting period, or plans to do so in the next. Log brand is the natural log of amounts payable for advertising and marketing services. Total software is the total cost of computer software programs and databases developed by own staff for business use or purchased externally. These variables should address potential omitted variable bias given prior evidence that intangible investments correlate with both technology adoption and complementary intangibles such as organizational capital (Bresnahan et al., 2002; Brynjolfsson and Hitt, 2000).

3.5 Summary statistics

Table A.2 presents summary statistics for our sample of 1,292 UK firms observed between 2020 and 2023, split between AI adopters (AI Use = 1) and non-adopters (AI Use = 0). We focus on baseline characteristics measured in 2020 to establish temporal precedence and mitigate concerns about reverse causality, as AI adoption in 2023 could itself influence contemporaneous firm characteristics.

AI adopters are recorded to have higher baseline management quality and higher labor productivity (£268,800 versus £193,500 per worker) in 2020. They also invest more heavily in complementary assets: brand spending in 2021, while software spending shows a similar pattern. Between 2020 and 2023, AI adopters experienced stronger growth in both turnover and employment (0.070 versus 0.016).

In terms of organizational structures, we find that adopters are more likely to operate multiple sites and show lower rates of centralized decision-making across recruitment, product development, and investment. Interestingly, R&D engagement in 2021 is less more common among adopters.

Table 4: Summary Statistics

	All	AI Use = 1	AI Use = 0	Diff
Adjusted management score 2020	0.594	0.610	0.586	0.024
	(0.163)	(0.157)	(0.165)	
Labor productivity 2020	217.5	268.8	193.5	75.276
	(1,026.3)	(1,603.1)	(588.2)	
Brand Spending 2021 (£,000)	548.5	1,358.7	210.4	1,148.314
	(4,420.1)	(8,026.1)	(742.6)	
Software Spending 2021 (£,000)	105.7	222.5	56.9	165.541
	(599.8)	(1,017.8)	(267.9)	
Multiple sites	0.444	0.482	0.427	0.055
	(0.497)	(0.500)	(0.495)	
Centralized recruitment	0.430	0.384	0.455	-0.071
	(0.496)	(0.488)	(0.499)	
Centralized product development	0.605	0.561	0.628	-0.067
	(0.489)	(0.498)	(0.484)	
Centralized investment decision	0.552	0.544	0.556	-0.012
	(0.498)	(0.499)	(0.497)	
R&D 2021	0.447	0.410	0.462	-0.052
	(0.498)	(0.494)	(0.499)	

Note: Table shows means with standard deviations in parentheses. The sample consists of 1,292 firms observed in 2020–2023. "AI Use = 1" denotes firms that report currently using at least one AI technology in their business processes in the latest survey wave. "AI Use = 0" denotes firms that report neither using AI nor planning to adopt it in the next 2024. "Difference" reports the raw difference in means between the two groups (AI Use = 1 minus AI Use = 0). Labor productivity is value added per worker (£'000). Brand Spending 2021 and Software Spending 2021 are in £'000. Δ Ln Turnover 2020–2023 and Δ Ln Employment 2020–2023 are log changes over the period. Adjusted management score 2020. Multiple sites, Centralized recruitment, Centralized product development, and Centralized investment decision, and R&D 2021 are shares (means of binary indicators).
Source: Office for National Statistics

Table 5: Conditional Technology Adoption Rates (Matched Panel Sample)

	Share of Firms Also Using (Y):				
Given Firm Uses (X):	AI	Cloud	Robotics	Software	Equipment
AI	—	93.3%	18.1%	88.7%	52.5%
Cloud	10.7%	—	9.6%	82.7%	54.9%
Robotics	18.3%	85.0%	—	91.9%	85.8%
Software	10.9%	88.7%	11.2%	—	62.3%
Equipment	9.5%	87.0%	15.4%	92.0%	—

Notes: Table shows percentage of firms using technology X (row) that also use technology Y (column). For example, 93.3% of AI adopters also use Cloud. Based on matched panel sample, 2020-2023.

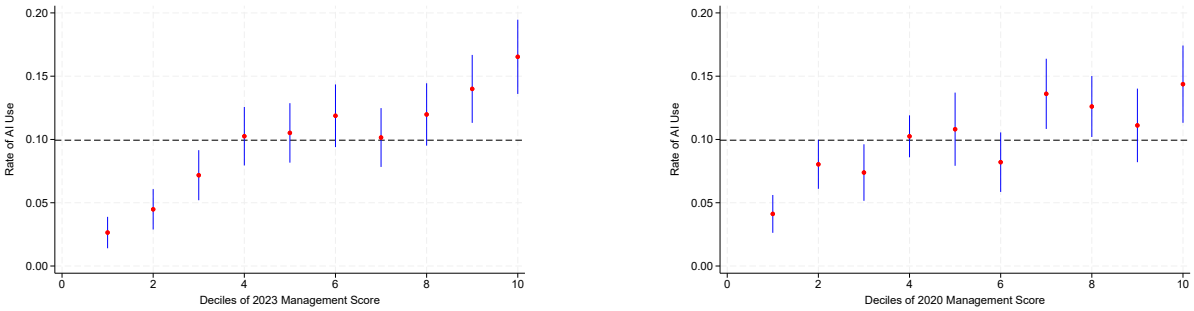
Table 5 presents conditional technology adoption rates from our matched panel sample. Each cell shows the percentage of firms using technology X (row) that also adopt technology Y (column). For example, reading across the AI row, 93.3% of AI adopters also use cloud computing, while 88.7% use specialized software. Conversely, reading down the AI column, only 10.7% of cloud adopters and 10.9% of software adopters use AI. This reading reveals strong but fundamentally asymmetric complementarities between AI and other ICT technologies.

AI adoption shows strong complementarity with cloud computing and specialized software. This could imply that enabling infrastructure must be in place before firms can effectively deploy AI systems. However, the fact that the inverse relationship is weak indicates that having complementary ICT infrastructure is necessary but far from sufficient for AI adoption. The vast majority of firms with cloud computing (89.3%) and specialized software (89.1%) do not adopt AI, pointing to substantial additional barriers beyond basic technological prerequisites. These patterns align closely with ONS (2023) data from the full cross-sectional samples (see Appendix table A.1).

Figure 1 shows AI adoption rates across deciles of the management score distribution for 2023 (panel 1a) and 2020 (panel 1b). We find a clear positive relationship between the management scores and AI adoption rates; panel 1b shows higher adoption rates for decile 9 and 10. Firms in the highest management decile adopt AI at rates roughly 10 percentage points higher than those in the lowest decile. Interestingly, in both figures, the adoption rate per decile exceeds the adoption rate for the full sample once firms go above the 50th percentile of management scores.

Overall, these patterns suggest that AI adoption is associated with better manage-

Figure 1: AI Adoption Rate per Decile of Management Score



(a) Management Score 2023

(b) Management Score 2020

Note: Figure 1 shows AI adoption rates across deciles of the management score distribution. Panel (1a) displays 2023 data; panel (1b) displays 2020 data. The horizontal dashed line indicates the overall AI adoption rate for the panel sample. Management scores are calculated from the Management and Expectations Survey (MES). Higher deciles represent firms with stronger management practices. We present the data for the full sample figure A.1.
Source: Authors' calculations, Office for National Statistics

ment practices, higher productivity, more complementary investment, and faster growth. Our regression analysis examines whether these relationships hold conditional on firm characteristics and fixed effects. It is important to note that we also observe a positive relationship between the management score and the adoption rate of other technologies (see figure A.4). In the succeeding sections, we provide a deeper examination of the relationship between management practices and AI adoption, investigating whether this relationship is specific to AI or reflects a general pattern across all technologies.

4 Empirical strategy

Our central research question is whether AI adoption requires greater organizational capital than other technologies. Our empirical approach exploits variation in management practices to test whether stronger managerial capabilities are required for AI adoption compared to other technologies. For our baseline specification, we estimate the linear probability model:

$$\Pr(AI = 1)_{i,1} = \beta_0 + \beta_1 M_{i,0} + \beta_2' X_{i,s,0} + \delta_z + \gamma_s + \varphi_\alpha + \rho_r + \varepsilon_{i,1} \tag{1}$$

where $\Pr(AI = 1)_{i,1}$ represents the probability that firm i adopts AI at time $t = 1$

(2023). The key explanatory variable is $M_{i,0}$, which captures firm i's management quality score measured in the baseline period $t = 0$ (2020). $X_{i,s,0}$ is a vector of firm-level controls measured at baseline, including log labor productivity, for firm i in industry s. The management score and all covariates are measured in the baseline year (2020) to mitigate concerns about reverse causality.

The model includes a set of fixed effects: δ_z denotes firm size category fixed effects, γ_s represents industry fixed effects at the 2-digit SIC level, φ_α captures firm age fixed effects, and ρ_r controls for regional fixed effects. These fixed effects account for systematic differences in AI adoption across firm size, industry, age, and geographic location. $\varepsilon_{i,1}$ is the idiosyncratic error term.

The coefficient of interest, β_1, measures the relationship between baseline management quality in 2020 and subsequent AI adoption in 2023, holding constant firm characteristics and the various fixed effects. A positive and significant β_1 coefficient shows that better-managed businesses are more likely to use AI, conditional on their size and other observables.

To confirm whether AI adoption requires greater mangerial capital compared to other technologies, we apply equation 1 to different technologies separately. In particular, we estimate the relationship between management practices and the probability of adopting cloud computing, robotics, specialized software, and specialized equipment. We then compare the coefficient β_1^{AI}, against the coefficient from the regression with other technologies. Our null hypothesis that that $\beta_1^{AI} = \beta_1^k$ for all technological assets k[9].

We also investigate mechanisms linking management capital to AI adoption through two analyses. First, we decompose the total management score into its component dimensions and re-estimate equation 1 for each sub-score separately, identifying which management practices most strongly predict adoption. Second, we augment the baseline specification with dummy variables capturing organizational structure characteristics (e.g., presence of centralization, decision-making authority), testing whether these structural features affect adoption conditional on management quality.

[9] k being cloud computing, robotics, specialized software, and specialized equipment

4.1 Robustness tests

To address concerns about sample selection, we estimate all specifications using contemporaneous variables from the 2023 MES wave. Our baseline analysis links the 2020 MES (for management practices) with the 2023 MES (for AI adoption), which necessarily reduces the sample size due to panel attrition. Since larger and better-managed firms are more likely to appear in both survey waves, this attrition could introduce bias if these firms also differ systematically in their propensity to adopt AI. The contemporaneous specification eliminates this concern by using only cross-sectional variation within the 2023 wave.[10] We find that our core results remain qualitatively unchanged, though the magnitude of coefficients is slightly larger, consistent with measurement error attenuation in the lagged specification.

We also examine the robustness of our findings to alternative functional forms and sample composition. First, we winsorize our management score variable at the 1st and 99th percentiles to ensure that outliers do not drive our results. Second, we re-estimate our models excluding one industry at a time to verify that our findings are not driven by sector-specific patterns in either management practices or AI adoption.

Finally, we employ propensity score matching as an alternative identification strategy. This approach addresses potential concerns about functional form misspecification in our baseline probit models and ensures that our results are not sensitive to the specific parametric assumptions imposed. We match firms on observable characteristics including size, age, industry, and productivity, then estimate the average treatment effect of above-median management scores on AI adoption.

5 Results

Results from our baseline regression described in the previous section show that firms with better management quality, as measured by the 2020 management score, are significantly more likely to have adopted AI in 2023 (see table 6) and are also more likely to report plans for adoption in 2024.

[10] Similar to the 2020 overall management score, our calculation excludes two survey items (questions 16b and 25) from the 2023 overall management score and their associated sub-components (Targets and Employment Practices).

Our results also show that foreign ownership does not show a significant relationship with AI adoption. Similarly, whether a firm is family-managed does not appear to be associated with AI adoption. Management practices remain positively and significantly associated with AI adoption even after controlling for complementary intangible investments (R&D, software, brand). The slightly larger coefficients among ABS-matched firms (see table A.12) suggest that organizational capital may matter more for AI adoption among larger enterprises where implementation complexity is greatest.

Table 6: Are firms with better managers more likely to adopt AI?

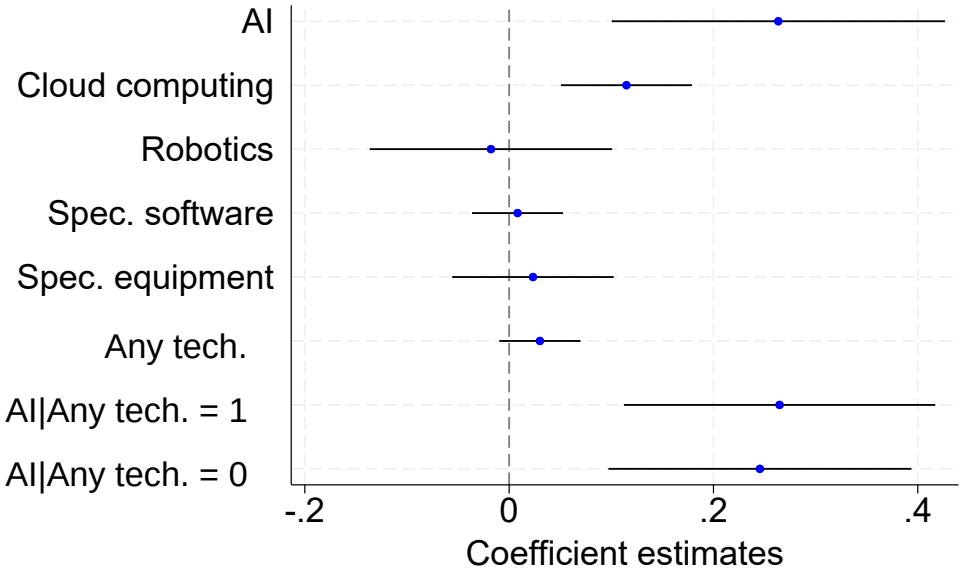
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Pr(AI = 1)					Pr(Plan AI = 1)		
Management Score 2020	0.242**	0.263**	0.267**	0.378***	0.380***	0.160**	0.139*	0.145*	0.136	0.136
	(2.68)	(3.06)	(3.06)	(6.98)	(6.94)	(2.68)	(2.03)	(2.13)	(1.22)	(1.22)
Log Labor Productivity 2020		-0.019	-0.018	-0.005	-0.008		0.019	0.022	0.004	0.004
		(-1.25)	(-1.14)	(-0.20)	(-0.34)		(1.15)	(1.23)	(0.26)	(0.28)
Foreign			-0.025		0.110			-0.039		-0.011
			(-0.88)		(1.46)			(-1.28)		(-0.12)
Family management status				-0.002	0.008				-0.016	-0.017
				(-0.03)	(0.14)				(-0.39)	(-0.44)
Observations	1292	1292	1292	789	789	881	881	881	518	518
Adj R2	0.023	0.024	0.023	0.034	0.035	0.017	0.017	0.017	-0.020	-0.022
Size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Note:*This table reports the results from linear probability models estimating the likelihood of AI adoption (columns 1-5) and plans to adopt AI (columns 6-10). The dependent variable in columns 1-5 equals 1 if the firm has adopted AI technology, and 0 otherwise. The dependent variable in columns 6-10 equals 1 if the firm plans to adopt AI, and 0 otherwise. Management Score 2020 is the overall management quality score from the MES 2020 survey. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. t-statistics are reported in parentheses. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' calculations, Office for National Statistics

Are these results unique to AI? The literature by Bresnahan et al. (2002) implies that organizational capital is required for the adoption of all ICTs. It is possible that the impact of our results does not apply specifically to AI, but to the adoption of all forms of IT investments.

To test this, we examine whether management practices similarly predict the adoption of other forms of technological capital available in the survey data, namely, cloud computing, robotics, specialized software, and specialized equipment. We also estimate whether management practices predict the probability of adopting at least one of these technologies.

Figure 2: Effect of Management Practices on Technology Adoption



Notes: Coefficient estimates with 95% confidence intervals for Management Score 2020 from linear probability models of technology adoption. Any tech refers to the adoption of any technology (other than AI). All specifications control for labor productivity and include firm size, industry, age, and region fixed effects. Full regression tables in Appendix Table A.3.

We find no evidence that management practices significantly affect the adoption of robotics, specialized software, or specialized equipment (see figure 2). While management practices do predict cloud computing adoption, the coefficient magnitude is less than half that observed for AI. However, this estimate for cloud computing is subjected to potential reverse causality. Cloud computing has been commercialized since 2002, prior to AI's much recent boom. Among MES respondents, 69% already use cloud computing systems and

applications in 2023. Nonetheless, the result might reflect something distinctive about the managerial requirements for implementing AI.

Moreover, when we condition on the adoption of other technologies, the estimated effect of management practices on AI adoption remains statistically significant and substantively unchanged. This result implies that even among firms with comparable technology portfolios, superior management practices continue to predict AI adoption. These findings suggest that the observed relationship between management practices and AI adoption does not merely reflect omitted firm-level capabilities associated with general technology adoption, but rather captures organizational characteristics specifically salient for AI implementation.

5.1 How management impacts AI adoption

To identify which aspects of good management are more associated with the probability of AI adoption, we run the same regression, but this time with the different components of the total management score. The MES management score is based on four subcomponents. Continuous improvement captures whether firms respond to problems reactively or through structured, forward-looking processes. Key performance indicators (KPIs) assess how many metrics are tracked and how often they are reviewed by both managers and staff. Targets measure how performance goals are set, communicated, and linked to incentives. Employment practices evaluate promotion criteria, training levels, and how underperformance is addressed. These component scores are averaged to form the overall management practices score.

We find that firms with more structured performance monitoring appear more likely to adopt AI (see table 7). In particular, those tracking a greater number of KPIs show a clear positive association with current AI adoption, suggesting that data-driven management practices may complement or enable technology integration. We also find that target-setting is also significantly associated with AI adoption. Firms with clearer or more established targets are more likely both to have adopted AI already and to plan future adoption. This indicates that goal-oriented management structures may help firms prepare for or benefit from AI.

Compared with other technologies, the magnitude and significance of these effects are notably stronger for AI. Figure 3 illustrates this by comparing the impact of each man-

agement practice component across different technologies. While KPI tracking and target exhibit much weaker and statistically insignificant relationships with robotics, specialized software, and specialized equipment adoption. For cloud computing, we observe moderate positive effects of monitoring practices, though still smaller in magnitude than for AI.

Table 7: Which element of management impacts AI adoption?

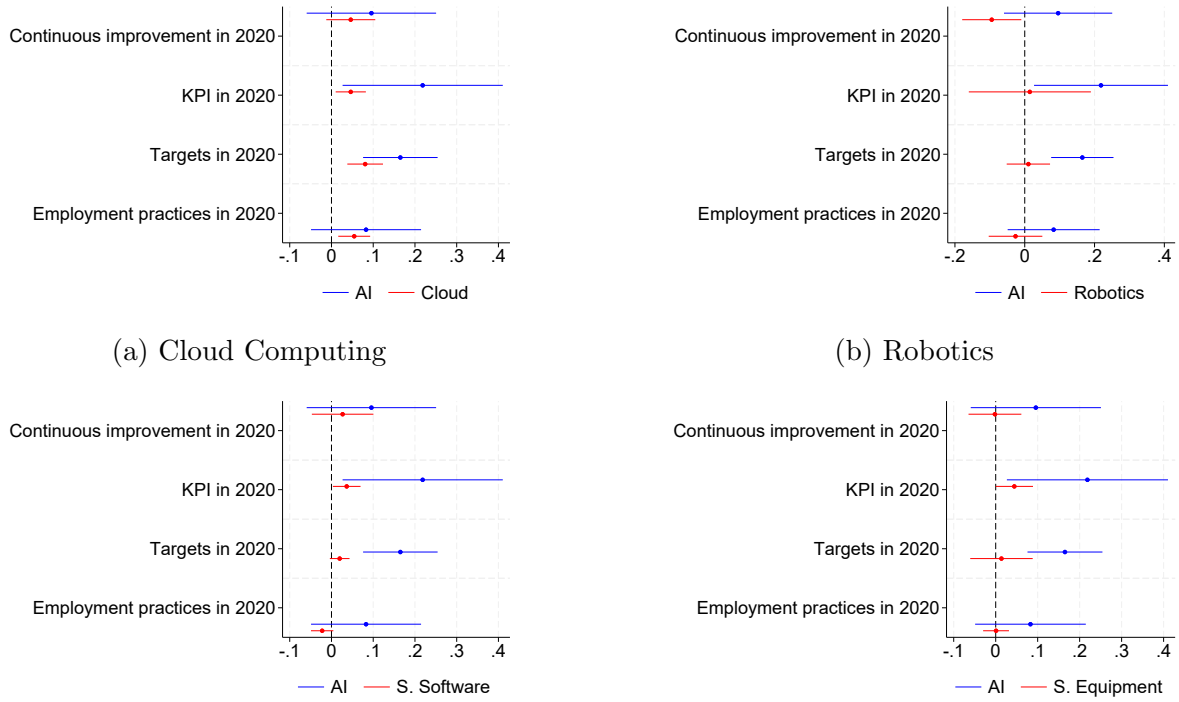
	(1)	(2)	(3)	(4)
		Pr(AI = 1)		
Continuous improvement in 2020	0.096			
	(1.17)			
KPI in 2020		0.219*		
		(2.16)		
Targets in 2020			0.165***	
			(3.50)	
Employment practices in 2020				0.083
				(1.19)
Log Labor Productivity 2020	-0.014	-0.016	-0.019	-0.015
	(-0.93)	(-1.02)	(-1.24)	(-0.95)
Observations	1292	1292	1292	1292
Adj R2	0.018	0.025	0.022	0.018
Size FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes

Note: This table reports the results from linear probability models estimating the likelihood of AI adoption. The dependent variable equals 1 if the firm has adopted AI technology, and 0 otherwise. Each column examines a different component of management practices measured in 2020. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. t-statistics are reported in parentheses. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Author's calculations, Office for National Statistics

More specifically, KPI tracking and target setting can help address two problems with technology deployment in the presence of organizational complementarities: the coordination problem and the tacit work 'culture' (Brynjolfsson and Milgrom, 2012). First, by making objectives, performance, and trade-offs observable, KPI tracking provides a common language and measurement framework for different actors to coordinate on deployment priorities; and to monitor where rent reallocations are needed. Second, implicit organizational 'culture' and rules of thumb used by employees may interfere with new

practices needed for AI. Target setting creates explicit expectations (who do what, by when) and helps shift tacit norms.

Figure 3: Which element of management impacts other technologies?



(a) Cloud Computing

(b) Robotics

(c) Specialize Software

(d) Specialized Equipment

Note: This figure displays coefficient estimates from linear probability models examining the relationship between individual management practice components (measured in 2020) and technology adoption (measured in 2023). Each panel compares AI adoption (red) with another technology: (a) cloud computing, (b) robotics, (c) specialized software, and (d) specialized equipment. Points represent coefficient estimates, and horizontal lines show 95% confidence intervals. Triangles indicate statistical significance at the 10% level or better; circles indicate non-significant estimates. All regressions include controls for firm size, industry (2-digit SIC), firm age, region, and log labor productivity. Standard errors are clustered at the industry level.
Source: Authors' calculations, Office for National Statistics

An alternative explanation is that these monitoring practices could be a proxy for a firm's level of data intensity or datafication (i.e. converting information into digital data), which is essential for maintaining and making the most out of AI models. This is particularly important in the pilot phase to justify value for the actual implementation.

When we control for the level data intensity[11], we find that our results still hold (see Appendix table ref A.5), which suggests that these specific practices impact adoption over and above the firm's general data infrastructure and analytical capabilities. This indicates that it is not merely digital readiness that facilitates AI adoption, but rather the specific organizational routines necessary to justify AI investments and guide implementation decisions.

Lastly on this topic, monitoring capabilities may also capture a business's control intensity over its workforce - an AI use case that is reportedly gaining traction (Mettler, 2024). Under this interpretation, firms that already prioritize workforce monitoring may be drawn to AI specifically for surveillance applications like productivity tracking or performance evaluation.

[11]The 2023 MES asked what types of data analyses the firm used to support decision-making in 2023. Respondents could indicate they used little to no analyses or select all options that applied (summary statistics; trends and comparisons across time periods; dashboards and interactive analysis; statistical or forecasting models; and algorithmic models). Data intensity is measured on a scale of 0 to 5, with 0 representing "little to no analyses" and 5 showing use of all listed types of data analyses.

Table 8: Organisational structures and AI adoption

	(1)	(2)	(3)	(4)
		Pr(AI = 1)		
Multiple sites	0.045			
	(1.53)			
Centralized recruitment		-0.052		
		(-1.25)		
Centralized product development			-0.056**	
			(-2.62)	
Centralized investment decision				-0.013
				(-0.45)
Management Score 2020	0.260**	0.346***	0.352***	0.372***
	(2.91)	(5.80)	(6.36)	(6.95)
Log Labor Productivity 2020	-0.020	-0.039***	-0.039***	-0.043***
	(-1.33)	(-3.93)	(-3.72)	(-4.37)
Observations	1292	574	574	556
Adj R2	0.025	0.020	0.021	0.025
Size FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes

Note: This table reports the results from linear probability models estimating the likelihood of AI adoption. The dependent variable equals 1 if the firm has adopted AI technology, and 0 otherwise. Management Score 2020 is the overall management quality score from the MES 2020 survey. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. t-statistics are reported in parentheses. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' calculations, Office for National Statistics

We also consider organizational structure, looking at whether indicators of centralization impact AI Adoption. The MES asks firms several questions on organizational structures, as discussed in section 3.2. Importantly, the centralization questions are only asked of firms operating across multiple sites in the UK, as single-site firms do not face organizational decisions about whether to centralize or decentralize authority across locations. This reduces our sample size for the organizational structure analysis.

The results in table 8 imply that conditional on having the same management scoree and labor productivity, firms with more decentralized product development are more likely to adopt AI technologies. Specifically, firms where product development decisions are cen-

tralized exhibit a significantly lower probability of AI adoption, as shown by the negative and statistically significant coefficient on Centralized product development (column 3).

This pattern aligns with the idea that AI adoption benefits from a specific organizational configuration. We interpret this as tentative evidence that successful AI adoption requires bottom-up identification of opportunities by technical teams who understand domain-specific applications, supported by a management infrastructure that enables coordination and monitoring of progress (Chatterji et al., 2025). At the same time, decentralized product development can proxy for broader organizational features such as innovation culture, product heterogeneity, or operational differences and complexity between sites. For example, firms operating under a franchising model may be sufficiently complex that experimentation with new technologies and product innovation occurs at the site level, independently of decentralization per se. In this case, the estimated relationship would reflect the underlying heterogeneity rather than a causal effect of decentralized decision-making.

We do not observe the same patterns for other technologies. For cloud computing (see table A.13), our results show that firms with multiple sites are more likely to adopt cloud computing programs. This likely reflects the practical need for cloud infrastructure to enable data sharing, centralized management systems, and real-time coordination across geographically for firms across dispersed locations. Meanwhile, we find that decentralized product development predicts robotics adoption (at 10% level), which mirrors results from AI. This could be because both technologies require domain-specific knowledge to identify valuable applications.

None of our measures of three centralization and organizational structure show any statistically impact of the adoption of specialized software (see table A.13). For specialized equipment, we find a marginally significant effect of decentralized recruitment, possibly because the skills required for operating specialized equipment are highly context-specific, and local managers with direct operational knowledge are better positioned to identify and recruit workers with the appropriate technical expertise.

These organizational structure findings should not be interpreted as causal effects. Unobserved factors may simultaneously influence both centralization decisions and technology adoption propensity. For example, exposure to intense competitive pressure might lead firms to both decentralize decision-making and adopt AI. Despite these identification limitations, our results provide valuable descriptive evidence on the organizational

characteristics of early AI adopters.

5.2 Robustness checks

Our findings remain robust across alternative samples and estimation strategies. Using the larger 2023 cross-sectional sample rather than the matched 2020-2023 panel yields comparable results. To address concerns about selection on observables, we employ propensity score matching methods comparing firms with high management quality to observably similar firms with lower management quality. Across four matching estimators[12], we consistently find that high management quality significantly increases AI adoption probability (see Appendix B for detailed results).

When we apply the same matching approach across technologies, high management quality significantly predicts only AI and cloud computing adoption, with no significant effects for robotics, specialized software, or specialized equipment, confirming that AI demands distinctive organizational capabilities. Finally, our results are not driven by outliers. Winsorizing management scores or labor productivity at various levels yields coefficients that remain statistically significant and consistent with our baseline estimates (Appendix B).

6 Discussion

Our results suggest that the role of structured management practices, as organizational complementarities, are technology-specific, with AI requiring a distinct managerial configuration not needed for other business technologies. We find that management practices strongly predict AI adoption but show no relationship with robotics, specialized software, or specialized equipment adoption, suggesting use of AI is related to structured measurement of performance. Moreover, AI adoption is more likely in firms with decentralized product development. These findings have important implications for technology diffusion theory, organizational economics, and innovation policy.

Both Hoffreumon et al. (2024) and Challapally et al. (2025) suggested that even "ready-made" AI tools still require significant internal development and customization. Struc-

[12]We apply propensity score matching, nearest-neighbor matching with one and three neighbors, and inverse probability weighting

tured management practices reduce the organizational costs of a complex and uncertain adoption process. For instance, the nascency of AI tools may require an iterative approach to piloting and implementation, demanding a management approach focusing on continuous improvement and problem-solving to navigate the learning curve. Additionally, a company's employment practices in 2020 shape the digital expertise needed to evaluate AI opportunities, identify use cases, and tailor AI tools to existing workflows. Monitoring capabilities (KPIs and target-tracking practices) address interdepartmental coordination problems in aligning the vision and goals for adoption, and may capture a company's datafication level (see 5.1). Tacitly, structurally managed firms might better anticipate and feel more confident tackling *ex-post* organizational changes to extract value from AI adoption (e.g. changes in worker composition, task structure, and tacit work practices).

We further propose three related explanations for the technology-specificity of our findings. First, AI systems require continuous monitoring, adjustment, and integration into workflows. Unlike robotics or specialized equipment, AI performance depends on ongoing feedback and refinement (Sculley et al., 2015). Machine learning models experience performance degradation over time as data distributions shift, requiring continuous monitoring and regular retraining (Datadog, 2024). Recent UK data from the Business Insights and Conditions Survey (BICS) shows the most popular use of AI by businesses is text generation with LLMs. Randomness and inconsistency in LLM outputs have generally been documented Wang and Wang (2025). This distinguishes LLMs from pre-programmed and ready-to-use technologies such as cloud-based services or specialized software.

Second, as AI system generates predictions, classifications, or recommendations that humans must interpret and act upon (Johnson et al., 2022), this creates ongoing coordination challenges that structured management practices help address. Firms need clear performance metrics to evaluate whether AI-generated insights are valuable and how they should be incorporated into business processes.

Third, AI applications are highly context-specific, making it difficult for central management to identify valuable use cases without domain knowledge (Storey et al., 2025). This may explain why decentralized product development predicts AI adoption, although this is a tentative hypothesis. Technical teams working directly with business processes are better positioned to recognize where AI can add value. However, these bottom-up initiatives require management infrastructure to succeed. Decentralized decision rights without structured monitoring may lead to fragmented, uncoordinated AI experiments

that fail to scale or deliver measurable value.

An alternative interpretation of our results is that, first, AI and other given technologies are at very different points in their maturity. For example, cloud computing is highly saturated with a 2023 adoption rate of around 70%, introducing a "ceiling effect" to our estimate. Second, technology maturity shifts binding constraints. The maturity of other technologies implies cost reduction, peer learning and vendor simplification, reducing the need for more structured management compared to nascent AI products.[13] The adoption decision might therefore lie more with business model fit, production volume, sub-sector competitive pressure, or the broader environmental contexts. For example, in 2025 the UK has an industrial robot density of 111 robots per 10,000 employees - making it the only G7 country to fall outside the top 20 (Richardson et al., 2025). This may suggest that the low and variable uptake of robotics across UK firms could reflect structural constraints such as the absence of a coherent national industrial strategy rather than heterogeneity in firm-level management quality.[14]

Our findings also extend and refine the organizational complementarities framework of Bresnahan et al. (2002). While Brynjolfsson and Hitt (2000) showed that IT demand depended on complementary organizational investments including decentralized decision-making, our results demonstrate that these complementarities might differ across individual technologies. The framework should not treat "technology" or even "IT" as monolithic categories but rather recognize that different technologies make different organizational demands.

This has implications for how to model technology adoption and diffusion. Standard adoption models emphasize factors like firm size, capital constraints, competitive pressure, and expected returns. Our results suggest these models must also account for management practices, the effect of which might vary by technology type. A firm may be organizationally ready to adopt robotics but not AI, or vice versa. This may help explain why technology diffusion patterns differ across innovations and why some firms successfully adopt certain technologies while struggling with others. It suggests that the standard definition

[13]The overall adoption rate of robotics, specialized software and specialized equipment in 2023 are 4%, 61% and 36% respectively.

[14]Our binary technology indicators only measure the extensive margin of adoption. For technologies that function as industry norms, the decision to adopt might largely be determined by operational necessity rather than management quality. Management practices may nonetheless influence the depth and sophistication of deployment, a margin our measure does not capture.

and measurement of organizational capabilities may need refinement to understand the likely adoption path of AI (Coyle, 2026 forthcoming)

It is important not to overstate these findings. At the time of our study, AI is a novel technology while the others were more established and well-integrated into business operations. Our results may partly capture the organizational costs of adopting an emerging technology under uncertainty, rather than the requirements for maintaining established technologies. Nevertheless, our results provide valuable insights into the organizational characteristics of early AI adopters and the management capabilities that enable adoption in the technology's initial diffusion phase. Understanding what distinguishes first movers offers important guidance for firms and policymakers seeking to accelerate AI adoption.

The technology-specificity of structured management capabilities also has implications for productivity measurement. If AI requires specific management practices to generate value, then studies estimating AI productivity effects must account for heterogeneity in managerial capabilities. Simple comparisons between AI adopters and non-adopters may confound the technology effect with organizational quality.

7 Policy implications and concluding remarks

Our findings suggest that policies to accelerate AI diffusion should address organizational capabilities, rather than focusing solely on financial barriers or technical skills. Our results imply that management capability-building programs should emphasize structured performance measurement systems. Generic management training may be less effective than targeted interventions focusing on KPIs, measurable targets, and data architecture. These capabilities appear to be the binding constraint for AI adoption, more so than for example continuous improvement processes or employment practices.

Moreover, policies should encourage organizational structures that empower technical teams while maintaining coordination infrastructure. Simply mandating AI adoption from the top down is unlikely to succeed if technical teams lack autonomy to identify valuable applications. But bottom-up experimentation without structured monitoring may lead to fragmented efforts that fail to scale. Policy interventions might include guidance on organizational design for AI adoption or support for developing internal coordination mechanisms. Some studies have suggested that while a decentralized structure facilitates the

initial adoption phase, centralization may encourage the actual implementation of technology innovation (Baker, 2012; Rogers, 2003). This corroborates the model by Agrawal et al. (2024) which shows that if complementary organizational changes are possible, AI adoption could generate higher synergistic pay-offs in non-modular organizations compared to modular ones.

Lastly, we believe technology-specificity of our findings suggests that different technologies require different policy approaches. Robotics adoption may respond well to capital subsidies or tax incentives, since these are primarily financial decisions that can be made centrally. AI adoption requires a different approach focused on organizational readiness. Blanket "technology adoption" policies that do not distinguish between technologies risk misallocating resources. Policymakers should assess what organizational capabilities each technology requires and target interventions accordingly.

More broadly, if management practices are the binding constraint on AI adoption, then the AI adoption gap may reflect deeper organizational weaknesses in the economy. Countries or regions with poor average management quality may struggle to benefit from AI, even with abundant capital and technical skills. This suggests that long-standing concerns about management quality in the UK have new urgency in the age of AI.

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A Additional results

Table A.1: Conditional Technology Adoption Rates, UK Firms 2023

	Share of firms also using technology Y (column)					
Given firm uses X (row):	AI	Cloud	Specialized Software	Robotics	Specialized Equipment	Only one technology
Artificial Intelligence	—	91%	83%	12%	43%	4%
Cloud Computing	11%	—	78%	5%	44%	17%
Specialized Software	12%	88%	—	6%	53%	5%
Robotics	25%	87%	86%	—	78%	2%
Specialized Equipment	10%	86%	91%	9%	—	2%

Source: Office for National Statistics, Business Insights and Conditions Survey (BICS), 2023.
Notes: Table shows the percentage of firms using technology X (row) that also use technology Y (column). For example, 91% of AI adopters also use cloud computing, while 11% of cloud adopters use AI..

Table A.2: Descriptive Statistics by AI Adoption Status

	All	AI Use = 1	AI Use = 0	Difference
Management Practices				
Continuous Improvement 2020	0.870	0.879	0.866	0.013
	(0.187)	(0.175)	(0.192)	
KPI 2020	0.485	0.504	0.476	0.028
	(0.199)	(0.199)	(0.199)	
Targets 2020	0.548	0.566	0.539	0.027
	(0.211)	(0.208)	(0.212)	
Employment Practices 2020	0.665	0.677	0.659	0.018
	(0.225)	(0.224)	(0.225)	
Other Intangible Capital				
Software Spending 2021 (£,000)	105.671	222.461	56.920	165.541
	(599.846)	(1,017.774)	(267.948)	
Software Spending 2022 (£,000)	102.872	145.471	85.482	59.989
	(787.854)	(664.086)	(833.331)	
R&D 2021	0.447	0.410	0.462	−0.052
	(0.498)	(0.494)	(0.499)	
R&D 2022	0.482	0.443	0.499	−0.056
	(0.500)	(0.498)	(0.501)	
Brand Spending 2021 (£,000)	548.533	1,358.679	210.364	1,148.314

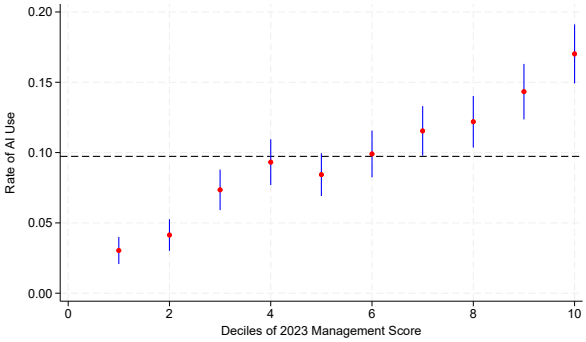
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Table A.2 – Continued from previous page

	All	AI Use = 1	AI Use = 0	Difference
	(4,420.110)	(8,026.086)	(742.633)	
Brand Spending 2022 (£,000)	572.485	1,373.683	245.420	1,128.263
	(4,324.272)	(7,881.630)	(852.101)	
Firm Size (Employment)				
10–19 employees	0.144	0.175	0.129	0.046
	(0.351)	(0.381)	(0.336)	
20–49 employees	0.310	0.280	0.325	−0.045
	(0.463)	(0.449)	(0.469)	
50–99 employees	0.255	0.243	0.260	−0.017
	(0.436)	(0.430)	(0.439)	
100–249 employees	0.168	0.170	0.167	0.003
	(0.374)	(0.376)	(0.373)	
250+ employees	0.123	0.131	0.119	0.012
	(0.329)	(0.338)	(0.324)	
Firm Age (Years)				
3–5 years	0.011	0.007	0.012	−0.005
	(0.104)	(0.085)	(0.111)	
6–10 years	0.080	0.090	0.075	0.015
	(0.271)	(0.287)	(0.263)	
11–20 years	0.247	0.290	0.227	0.063
	(0.431)	(0.454)	(0.419)	
20+ years	0.663	0.613	0.686	−0.072
	(0.473)	(0.488)	(0.465)	

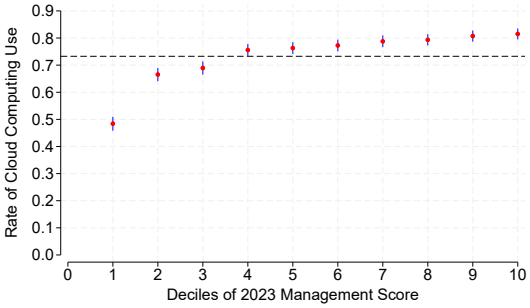
Notes: This table presents descriptive statistics for the full sample and by AI adoption status. For continuous variables, means are reported with standard deviations in parentheses. For binary and categorical variables, proportions are reported with standard deviations in parentheses. The Difference column shows the mean/proportion difference between AI adopters and non-adopters. The sample includes firms from the merged 2020-2023 MES panel.

Figure A.1: Management Score 2023, Full Sample

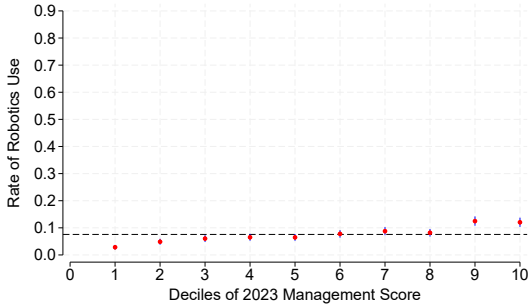


Note: Figure shows AI adoption rates across deciles of the management score distribution for the full sample in 2023. The horizontal dashed line indicates the overall AI adoption rate for the panel sample. Management scores are calculated from the Management and Expectations Survey (MES). Higher deciles represent firms with stronger management practices.
Source: Authors' calculations, Office for National Statistics.

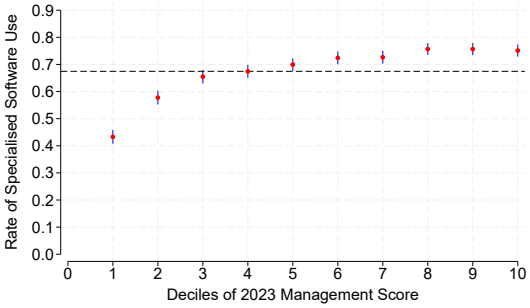
Figure A.2: Technology Adoption and 2023 Management Score, Full Sample



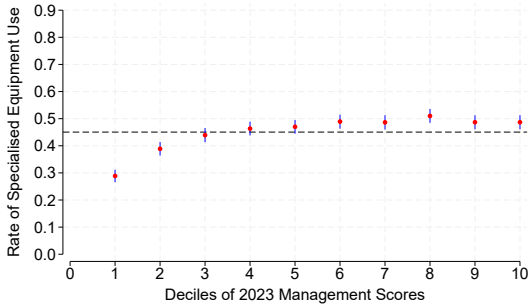
(a) Cloud Computing Adoption Rates



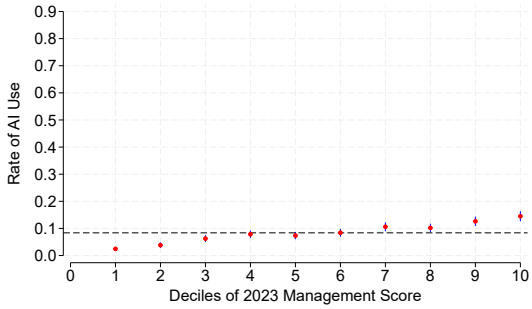
(b) Robotics Adoption Rates



(c) Specialized Software Adoption Rates



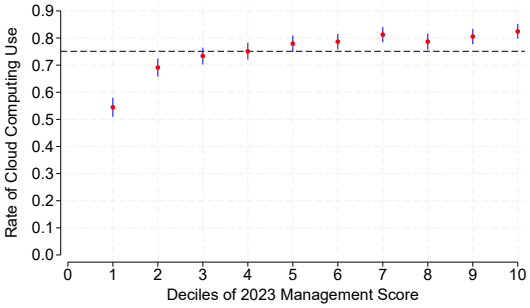
(d) Specialized Equipment Adoption Rates



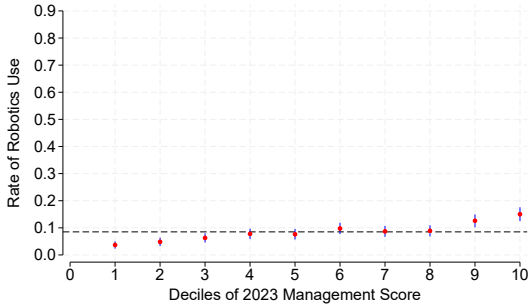
(e) AI Adoption Rates

Note: This figure displays technology adoption rates across deciles of the 2023 management score distribution for the full sample. Each panel shows adoption rates for a different technology: (a) cloud computing, (b) robotics, (c) specialized software, (d) specialized equipment, and (e) artificial intelligence. Points represent the share of firms in each management decile that have adopted the respective technology, with vertical lines showing 95% confidence intervals. The horizontal dashed line indicates the overall adoption rate for each technology across the sample.
Source: Authors' calculations, Office for National Statistics.

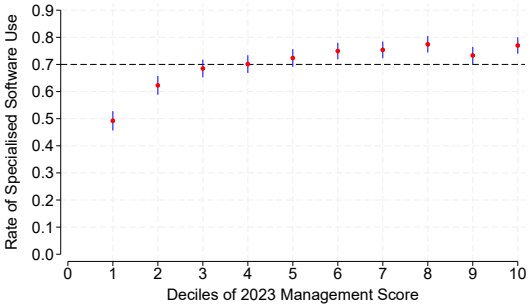
Figure A.3: Technology Adoption and 2023 Management Score, Merged Data 2020–2023



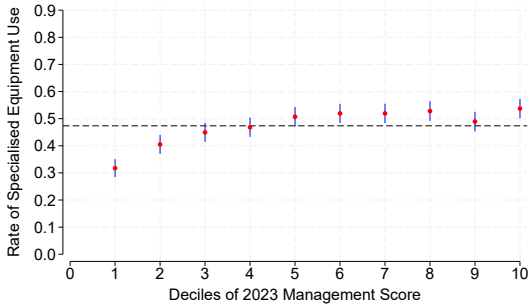
(a) Cloud Computing Adoption Rates



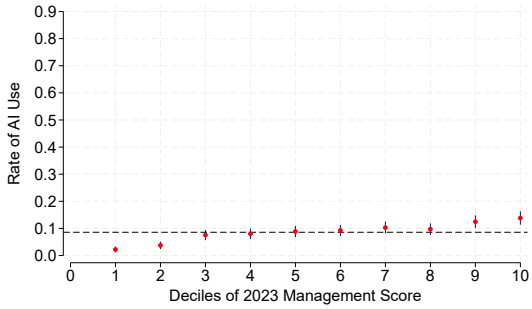
(b) Robotics Adoption Rates



(c) Specialized Software Adoption Rates



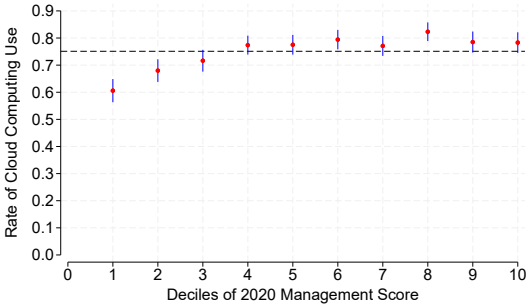
(d) Specialized Equipment Adoption Rates



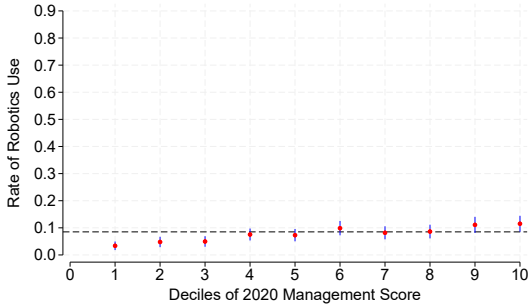
(e) AI Adoption Rates

Note: This figure displays technology adoption rates across deciles of the 2023 management score distribution for the linked dataset. Each panel shows adoption rates for a different technology: (a) cloud computing, (b) robotics, (c) specialized software, (d) specialized equipment, and (e) artificial intelligence. Points represent the share of firms in each management decile that have adopted the respective technology, with vertical lines showing 95% confidence intervals. The horizontal dashed line indicates the overall adoption rate for each technology across the sample.
Source: Authors' calculations, Office for National Statistics.

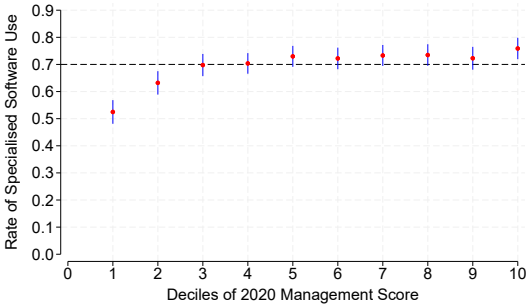
Figure A.4: Technology Adoption and 2020 Management Score, Merged Data 2020–2023



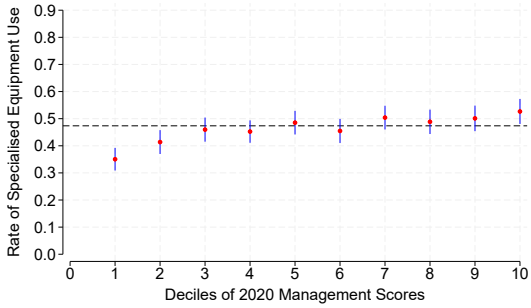
(a) Cloud Computing Adoption Rates



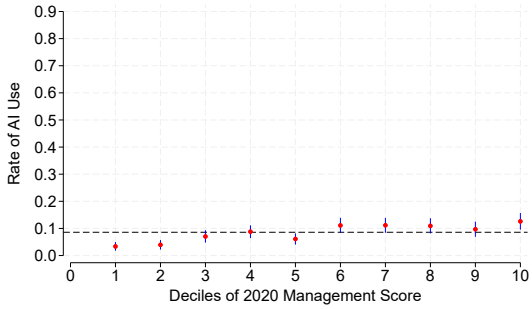
(b) Robotics Adoption Rates



(c) Specialized Software Adoption Rates



(d) Specialized Equipment Adoption Rates



(e) AI Adoption Rates

Note: This figure displays technology adoption rates across deciles of the 2020 management score distribution for the linked dataset. Each panel shows adoption rates for a different technology: (a) cloud computing, (b) robotics, (c) specialized software, (d) specialized equipment, and (e) artificial intelligence. Points represent the share of firms in each management decile that have adopted the respective technology, with vertical lines showing 95% confidence intervals. The horizontal dashed line indicates the overall adoption rate for each technology across the sample.
Source: Authors' calculations, Office for National Statistics.

Table A.3: Technology Adoption and Management Practices: Cross-Technology Comparison

	(1) Pr(Cloud=1)	(2) Pr(Robotics=1)	(3) Pr(S. Softwr=1)	(4) Pr(Eqpt=1)	(5) Pr(Other tech.=1)	(6) Pr(AI=1)	(7) Pr(AI=1 | Other tech. = 1)
Management Score 2020	0.115**	−0.018	0.008	0.023	0.030	0.245**	0.265**
	(3.39)	(−0.28)	(0.35)	(0.56)	(1.44)	(3.14)	(3.29)
Log Labor Productivity 2020	−0.002	0.040**	0.008***	0.013	0.003	−0.018	−0.017
	(−0.54)	(2.46)	(4.90)	(1.09)	(1.39)	(−1.08)	(−1.00)
Any Other Technology						0.285***	
						(7.08)	
Observations	3,960	973	3,658	2,562	4,307	1,269	1,197
Adjusted R^2	0.012	0.084	0.004	0.003	0.004	0.043	0.025
Size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports linear probability model estimates comparing the relationship between management practices and adoption across different technologies. Columns (1)-(5) examine cloud computing, robotics, specialized software, specialized equipment, and any non-AI technology. Columns (6) examine AI adoption, with column (6) controlling for general technology adoption. Column (7) drops all firms that do not adopt any of the other technologies. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Which element of management impacts cloud computing and robotics adoption?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pr(Cloud = 1)				Pr(Robot = 1)			
Continuous improvement in 2020	0.0462				-0.0945*			
	(0.0310)				(0.0447)			
KPI in 2020		0.0462**				0.0146		
		(0.0191)				(0.0923)		
Adjusted targets subscore in 2020			0.0807***				0.0104	
			(0.0226)				(0.0328)	
Adjusted employment practices subscore in 2020				0.0544**				-0.0264
				(0.0202)				(0.0406)
Log Labour Productivity 2020	0.000190	0.000129	-0.00248	-0.000465	0.0417**	0.0390**	0.0386*	0.0397**
	(0.00422)	(0.00418)	(0.00470)	(0.00399)	(0.0161)	(0.0165)	(0.0164)	(0.0166)
Constant	0.884***	0.902***	0.896***	0.892***	0.267**	0.191*	0.194*	0.212**
	(0.0204)	(0.0137)	(0.0140)	(0.0178)	(0.0968)	(0.100)	(0.0824)	(0.0889)
Observations	3960	3960	3959	3960	973	973	973	973
R-squared	0.014	0.014	0.018	0.016	0.109	0.108	0.108	0.108
Adj R2	0.00782	0.00795	0.0115	0.00941	0.0850	0.0838	0.0838	0.0840
Size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the results from linear probability models estimating the likelihood of cloud computing adoption (columns 1-4) and robotics adoption (columns 5-8). The dependent variable in columns 1-4 equals 1 if the firm has adopted cloud computing, and 0 otherwise. The dependent variable in columns 5-8 equals 1 if the firm has adopted robotics, and 0 otherwise. Each column examines a different component of management practices measured in 2020. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. Standard errors are clustered at the industry level. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' calculations, Office for National Statistics

Table A.5: Which element of management impacts specialized software and equipment adoption?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pr(S. Software = 1)				Pr(S. Equipment = 1)			
Continuous improvement in 2020	0.0267				-0.00178			
	(0.0389)				(0.0332)			
KPI in 2020		0.0365*				0.0444		
		(0.0175)				(0.0235)		
Adjusted targets subscore in 2020			0.0197				0.0137	
			(0.0124)				(0.0393)	
Adjusted employment practices subscore in 2020				-0.0223				0.000865
				(0.0141)				(0.0163)
Log Labour Productivity 2020	0.00797***	0.00779***	0.00760***	0.00897***	0.0134	0.0125	0.0128	0.0134
	(0.00166)	(0.00187)	(0.00169)	(0.00151)	(0.0118)	(0.0112)	(0.0120)	(0.0116)
Constant	0.868***	0.875***	0.883***	0.901***	0.820***	0.802***	0.815***	0.819***
	(0.0328)	(0.00789)	(0.00933)	(0.0123)	(0.0537)	(0.0592)	(0.0526)	(0.0546)
Observations	3658	3658	3657	3658	2562	2562	2561	2562
R-squared	0.011	0.011	0.011	0.011	0.013	0.013	0.013	0.013
Adj R2	0.00396	0.00436	0.00386	0.00403	0.00243	0.00319	0.00249	0.00242
Size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the results from linear probability models estimating the likelihood of specialized software adoption (columns 1-4) and specialized equipment adoption (columns 5-8). The dependent variable in columns 1-4 equals 1 if the firm has adopted specialized software, and 0 otherwise. The dependent variable in columns 5-8 equals 1 if the firm has adopted specialized equipment, and 0 otherwise. Each column examines a different component of management practices measured in 2020. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. Standard errors clustered at the industry level are reported in parentheses. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' calculations, Office for National Statistics

Table A.6: Changing the definition of adoption

	(1)	(2)	(3)
		Pr(AI = 1)	
Management Score 2020	0.206***	0.340***	-0.146
	(4.51)	(3.91)	(-0.95)
Ln Labor Productivity 2020	0.002	-0.011	-0.020
	(0.36)	(-0.88)	(-1.60)
Observations	3815	1730	849
Adj R2	0.034	0.030	0.010
Size FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes

Note: This table reports linear probability model estimates examining the robustness of the relationship between management quality and AI adoption to alternative definitions of AI adoption. In column 1, the dependent variable equals 1 if the firm has adopted AI, and 0 otherwise, where non-adopters include firms that indicated AI is not applicable to their processes. In column 2, the dependent variable equals 1 if the firm is either using AI or testing/piloting AI, and 0 otherwise. In column 3, the sample is restricted to AI-engaged firms only, where the dependent variable equals 1 if the firm is using AI as part of their processes, and 0 if the firm is testing or piloting AI. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. t-statistics in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' calculations, Office for National Statistics

Table A.7: Cloud Computing Adoption: Comparing User Groups

	(1) Users vs Non-Users & NA	(2) Users & Testers vs Non-Users	(3) Users vs Testers
Management Score 2020	0.299***	0.109**	−0.008
	(0.0318)	(0.0324)	(0.0206)
Log Labor Productivity 2020	0.0113*	−0.0023	0.0004
	(0.00531)	(0.00425)	(0.00492)
Constant	0.622***	0.878***	0.938***
	(0.0364)	(0.0143)	(0.0305)
Observations	4,381	4,211	3,910
R-squared	0.042	0.017	0.007
Adjusted R^2	0.0361	0.0113	0.0008
Size FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes

Notes: This table compares cloud computing adoption across different user groups. Column (1) compares users to non-users and firms where cloud is not applicable. Column (2) compares users and testers to non-users. Column (3) compares users to testers only. Management Score 2020 excludes questions 11b and 25 due to potential coding errors. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.8: Robotics Adoption: Comparing User Groups

	(1) Users vs Non-Users & NA	(2) Users & Testers vs Non-Users	(3) Users vs Testers
Management Score 2020	0.0652*	0.0434	−0.0925
	(0.0283)	(0.101)	(0.121)
Log Labor Productivity 2020	0.0163***	0.0347*	0.0215
	(0.00373)	(0.0167)	(0.0116)
Constant	−0.0200	0.265**	0.697***
	(0.0296)	(0.0976)	(0.0749)
Observations	4,241	1,101	501
R-squared	0.118	0.090	0.101
Adjusted R^2	0.112	0.0684	0.0521
Size FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes

Notes: This table compares robotics adoption across different user groups. Column (1) compares users to non-users and firms where robotics is not applicable. Column (2) compares users and testers to non-users. Column (3) compares users to testers only. Management Score 2020 excludes questions 11b and 25 due to potential coding errors. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.9: Specialized Software Adoption: Comparing User Groups

	(1) Users vs Non-Users & NA	(2) Users & Testers vs Non-Users	(3) Users vs Testers
Management Score 2020	0.299***	0.0095	−0.0303
	(0.0273)	(0.0238)	(0.0218)
Log Labor Productivity 2020	0.0319***	0.0076***	0.0040
	(0.00671)	(0.00168)	(0.00336)
Constant	0.472***	0.891***	0.941***
	(0.0360)	(0.0146)	(0.0214)
Observations	4,365	3,867	3,599
R-squared	0.050	0.010	0.005
Adjusted R^2	0.0447	0.0032	−0.0023
Size FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes

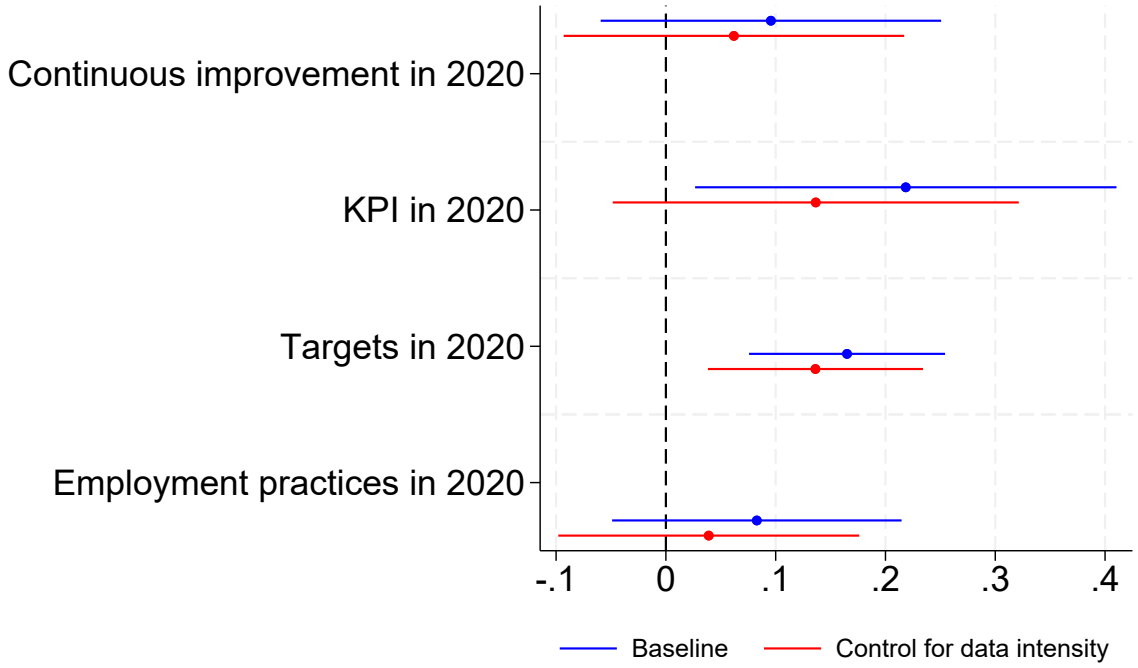
Notes: This table compares specialized software adoption across different user groups. Column (1) compares users to non-users and firms where specialized software is not applicable. Column (2) compares users and testers to non-users. Column (3) compares users to testers only. Management Score 2020 excludes questions 11b and 25 due to potential coding errors. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.10: Specialized Equipment Adoption: Comparing User Groups

	(1) Users vs Non-Users & NA	(2) Users & Testers vs Non-Users	(3) Users vs Testers
Management Score 2020	0.163**	0.0234	−0.0122
	(0.0650)	(0.0391)	(0.0263)
Log Labor Productivity 2020	0.0293***	0.0109	0.0095
	(0.00609)	(0.0105)	(0.00509)
Constant	0.316***	0.826***	0.889***
	(0.0360)	(0.0508)	(0.0220)
Observations	4,210	2,745	2,439
R-squared	0.112	0.010	0.019
Adjusted R^2	0.106	0.0009	0.0088
Size FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes

Notes: This table compares specialized equipment adoption across different user groups. Column (1) compares users to non-users and firms where specialized equipment is not applicable. Column (2) compares users and testers to non-users. Column (3) compares users to testers only. Management Score 2020 excludes questions 11b and 25 due to potential coding errors. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A.5: Controlling for Data Intensity



Note: This figure reports the results from coefficient plots of linear probability models estimating the likelihood of AI adoption. Blue reflects the coefficient estimates from the baseline model, while red controls for data intensity. Data intensity is measured on a scale of 0 to 5, with 5 representing the highest level of data intensity. dependent variable equals 1 if the firm has adopted AI technology, and 0 otherwise. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. Full results are in table A.11.
Source: Authors' calculations, Office for National Statistics

Table A.11: Management Practice Subscores and AI Adoption

	Dependent Variable: AI Use in 2023							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Continuous improvement 2020	0.0956	0.0619						
	(0.0818)	(0.0819)						
KPI tracking 2020			0.219*	0.137				
			(0.101)	(0.0976)				
Target setting 2020					0.165***	0.136**		
					(0.0471)	(0.0517)		
Employment practices 2020							0.0828	0.0390
							(0.0696)	(0.0723)
Data intensity		0.051***		0.046***		0.049***		0.050***
		(0.009)		(0.008)		(0.010)		(0.010)
Log labour productivity 2020	−0.014	−0.024	−0.016	−0.024	−0.020	−0.028	−0.015	−0.024
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)
Constant	0.299**	0.254*	0.283**	0.254**	0.322***	0.262**	0.328***	0.283***
	(0.119)	(0.116)	(0.109)	(0.107)	(0.080)	(0.084)	(0.076)	(0.074)
Observations	1,292	1,275	1,292	1,275	1,292	1,275	1,292	1,275
R-squared	0.038	0.055	0.044	0.057	0.042	0.058	0.038	0.055
Adjusted R^2	0.018	0.034	0.025	0.037	0.022	0.038	0.018	0.034
Fixed effects	Size, Industry, Age, Region							

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is binary indicator for AI adoption in 2023. Management practice subscores measured in 2020. Even-numbered columns include data intensity control.

Table A.12: AI Adoption and Other Intangible Capital

	Dependent Variable: Pr(AI = 1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total Management Score 2020	0.272**	0.253**	0.271**	0.244**	0.425***	0.436***	0.461***	0.416***
	(0.0962)	(0.0954)	(0.0896)	(0.0865)	(0.110)	(0.1000)	(0.0970)	(0.111)
Log Labor Productivity 2020	−0.0245	−0.0153	−0.0343	−0.0246	−0.00811	0.00193	0.00452	0.0120
	(0.0216)	(0.0231)	(0.0193)	(0.0217)	(0.0339)	(0.0331)	(0.0407)	(0.0387)
Total Software 2022	1.40e−05			−7.34e−07				
	(1.82e−05)			(1.35e−05)				
R&D 2022		−0.113**		−0.114***				
		(0.0329)		(0.0266)				
Log Brand 2022			0.0249***	0.0247***				
			(0.00427)	(0.00347)				
Total Software 2021					9.15e−05**			8.22e−05**
					(3.30e−05)			(3.28e−05)
R&D 2021						−0.106***		−0.120***
						(0.0222)		(0.0162)
Log Brand 2021							0.0153	0.0127**
							(0.00813)	(0.00516)
Observations	514	514	470	470	472	472	427	427
Adjusted R^2	0.0342	0.0460	0.0521	0.0601	0.0560	0.0530	0.0548	0.0779
Size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports linear probability model estimates examining the relationship between management quality and AI adoption, controlling for other intangible capital investments. Columns (1)-(4) use 2022 ABS data; columns (5)-(8) use 2021 ABS data. Total Software measures expenditure on computer software and databases (£,000). R&D is a binary indicator for in-house research and development activity. Log Brand is the natural logarithm of expenditure on advertising and marketing services. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.13: Organisational structures and technology adoption: Cloud computing and robotics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pr(Cloud = 1)				Pr(Robotics = 1)			
Multiple sites	0.0169**				0.0147			
	(0.00558)				(0.0226)			
Centralized recruitment		-0.0116				-0.105		
		(0.0214)				(0.0795)		
Centralized product development			-0.00592				-0.0791*	
			(0.0140)				(0.0394)	
Centralized investment decision				0.0212				-0.000402
				(0.0203)				(0.0562)
Log Labor Productivity 2020	-0.00282	-0.00244	-0.00247	-0.00206	0.0394**	0.0380	0.0369	0.0384
	(0.00444)	(0.00668)	(0.00676)	(0.00666)	(0.0158)	(0.0233)	(0.0234)	(0.0242)
Management Score 2020	0.113***	0.106*	0.107**	0.109**	-0.0196	0.103	0.111	0.0963
	(0.0338)	(0.0450)	(0.0450)	(0.0442)	(0.0599)	(0.112)	(0.107)	(0.105)
Observations	3960	1674	1674	1674	973	382	382	382
Adj R2	0.0127	0.0111	0.0107	0.0118	0.0831	0.0606	0.0558	0.0498
Size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the results from linear probability models estimating the likelihood of cloud computing adoption (columns 1-4) and robotics adoption (columns 5-8). The dependent variable in columns 1-4 equals 1 if the firm has adopted cloud computing, and 0 otherwise. The dependent variable in columns 5-8 equals 1 if the firm has adopted robotics, and 0 otherwise. Management Score 2020 is the overall management quality score from the MES 2020 survey. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. Robust standard errors are reported in parentheses. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Authors' calculations, Office for National Statistics

Table A.14: Organisational structures and technology adoption: Specialized software and equipment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pr(S. Software = 1)				Pr(S. Equipment = 1)			
Multiple sites	-0.00307				0.000299			
	(0.00675)				(0.0114)			
Centralized recruitment		-0.00491				-0.0246*		
		(0.0120)				(0.0128)		
Centralized product development			-0.0100				-0.0128	
			(0.00836)				(0.0118)	
Centralized investment decision				0.0184				0.0236
				(0.0246)				(0.0263)
Log Labor Productivity 2020	0.00823***	-0.00399	-0.00385	-0.00348	0.0126	0.0121	0.0119	0.0124
	(0.00156)	(0.00703)	(0.00698)	(0.00643)	(0.0115)	(0.0195)	(0.0195)	(0.0193)
Management Score 2020	0.00853	0.0208	0.0207	0.0214	0.0233	0.0941**	0.0997**	0.0977**
	(0.0234)	(0.0432)	(0.0431)	(0.0431)	(0.0423)	(0.0359)	(0.0359)	(0.0357)
Observations	3658	1537	1537	1537	2562	1080	1080	1080
Adj R2	0.00334	0.00545	0.00574	0.00622	0.00217	0.0212	0.0202	0.0208
Size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the results from linear probability models estimating the likelihood of specialized software adoption (columns 1-4) and specialized equipment adoption (columns 5-8). The dependent variable in columns 1-4 equals 1 if the firm has adopted specialized software, and 0 otherwise. The dependent variable in columns 5-8 equals 1 if the firm has adopted specialized equipment, and 0 otherwise. Management Score 2020 is the overall management quality score from the MES 2020 survey. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. Robust standard errors are reported in parentheses. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: Authors' calculations, Office for National Statistics

B Robustness checks

Table B.15: Adopt AI and Management Practices

	(1) Pr(AI=1)	(2) Pr(AI=1)	(3) Pr(AI=1)	(4) Pr(AI=1)	(5) Pr(AI=1)
Management Score 2023	0.288***	0.292***	0.297***	0.320**	0.324**
	(3.62)	(3.66)	(3.63)	(3.25)	(3.33)
Log Labor Productivity 2023		−0.003	−0.002	−0.017**	−0.015**
		(−1.10)	(−0.63)	(−3.39)	(−2.93)
Foreign Ownership			−0.029**		−0.074***
			(−2.53)		(−3.66)
Family Management				−0.010	−0.017
				(−0.37)	(−0.57)
Constant	0.081	0.093	0.087	0.134**	0.130*
	(1.61)	(1.82)	(1.61)	(2.39)	(2.30)
Size FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	2,495	2,495	2,495	1,464	1,464
Adjusted R^2	0.019	0.018	0.018	0.016	0.017

Notes: This table reports linear probability model estimates examining the relationship between management practices and AI adoption. The dependent variable equals 1 if the firm uses AI in its processes or methods in 2023, 0 otherwise. Management Score 2023 is the overall management quality score from the 2023 MES survey. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.16: Plans to Adopt AI and Management Practices

	(1) Pr(Plan AI=1)	(2) Pr(Plan AI=1)	(3) Pr(Plan AI=1)	(4) Pr(Plan AI=1)	(5) Pr(Plan AI=1)
Management Score 2023	0.288***	0.292***	0.297***	0.320**	0.324**
	(3.62)	(3.66)	(3.63)	(3.25)	(3.33)
Log Labor Productivity 2023		−0.003	−0.002	−0.017**	−0.015**
		(−1.10)	(−0.63)	(−3.39)	(−2.93)
Foreign Ownership			−0.029**		−0.074***
			(−2.53)		(−3.66)
Family Management				−0.010	−0.017
				(−0.37)	(−0.57)
Constant	0.081	0.093	0.087	0.134**	0.130*
	(1.61)	(1.82)	(1.61)	(2.39)	(2.30)
Size FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	2,495	2,495	2,495	1,464	1,464
Adjusted R^2	0.019	0.018	0.018	0.016	0.017

Notes: This table reports linear probability model estimates examining the relationship between management practices and plans to adopt AI in 2024. The dependent variable equals 1 if the firm plans to adopt AI, 0 otherwise. Management Score 2023 is the overall management quality score from the 2023 MES survey. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.17: Management Practice Sub-Components and AI Adoption

	(1) Pr(AI=1)	(2) Pr(AI=1)	(3) Pr(AI=1)	(4) Pr(AI=1)	(5) Pr(AI=1)	(6) Pr(Plan AI=1)	(7) Pr(Plan AI=1)	(8) Pr(Plan AI=1)	(9) Pr(Plan AI=1)	(10) Pr(Plan AI=1)
Continuous Improvement 2023	0.247***				0.211***	0.086**				0.032
	(7.21)				(5.71)	(2.51)				(0.80)
KPI 2023		0.200***			0.125**		0.150**			0.079
		(4.43)			(2.52)		(3.45)			(1.72)
Targets 2023			0.184***		0.131***			0.140**		0.091
			(4.87)		(3.75)			(2.64)		(1.69)
Employment Practices 2023				0.028	−0.075**				0.149**	0.102*
				(1.00)	(−2.83)				(3.22)	(1.92)
Log Labor Productivity 2023	−0.008	−0.010	−0.010	−0.006	−0.013*	0.001	−0.001	−0.002	0.001	−0.003
	(−1.31)	(−1.65)	(−1.75)	(−1.08)	(−2.06)	(0.35)	(−0.40)	(−0.52)	(0.34)	(−1.07)
Size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,698	3,698	3,698	3,698	3,698	2,495	2,495	2,495	2,495	2,495
Adjusted R^2	0.033	0.029	0.030	0.024	0.038	0.012	0.014	0.015	0.015	0.017

Notes: This table examines which management practice sub-components drive AI adoption using 2023 survey data. Columns (1)-(5) examine current AI adoption; columns (6)-(10) examine plans to adopt AI. Column (5) and (10) include all sub-components simultaneously. Each sub-component includes: Continuous Improvement (monitoring systems), KPI (key performance indicators), Targets (target-setting practices), and Employment Practices (hiring and retention practices). All sub-component scores range from 0 to 1, with higher values indicating better management practices. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.18: Organizational Structure and AI Adoption

	(1) Pr(AI=1)	(2) Pr(AI=1)	(3) Pr(AI=1)	(4) Pr(AI=1)	(5) Pr(AI=1)
Multiple Sites	0.021*				
	(1.98)				
Centralized Recruitment		−0.018			0.011
		(−0.69)			(0.31)
Centralized Product Dev.			−0.043**		−0.101*
			(−2.60)		(−2.24)
Centralized Investment				−0.008	0.071
				(−0.42)	(1.70)
Management Score 2023	0.277***	0.381***	0.376***	0.382***	0.386***
	(4.77)	(5.12)	(5.18)	(4.69)	(5.03)
Log Labor Productivity 2023	−0.010	−0.005	−0.004	−0.004	−0.004
	(−1.87)	(−0.63)	(−0.56)	(−0.44)	(−0.37)
Size FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	3,698	1,558	1,558	1,495	1,495
Adjusted R^2	0.030	0.023	0.025	0.027	0.029

Notes: This table examines how organizational structure affects AI adoption. Multiple Sites is a binary indicator for firms with multiple locations. Centralized variables indicate whether decisions about recruitment, product development, or investment are made centrally (vs. decentralized to individual sites). Column (5) includes all organizational structure variables simultaneously. Sample sizes vary because organizational structure questions are only asked of multi-site firms. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.19: Propensity Score Matching: Effect of High Management Quality on AI Adoption

	(1) P-Score	(2) NN(1)	(3) NN(3)	(4) IPW
ATET	0.102**	0.065*	0.061**	0.053*
	(2.05)	(1.73)	(2.41)	(1.90)
Potential Outcome Mean (Control)			0.275***	0.275***
			(12.50)	(10.83)
Observations	2,039	2,039	2,039	2,039
Size FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes

Notes: This table reports propensity score matching estimates of the effect of high management quality on AI adoption. High Management Score 2020 is a binary indicator for firms in the top half of the management score distribution. Column (1) reports kernel propensity score matching; column (2) reports nearest-neighbor matching with one neighbor; column (3) reports nearest-neighbor matching with three neighbors; column (4) reports inverse probability weighting. The potential outcome mean shows the predicted AI adoption rate for firms with low management scores. All specifications control for log labour productivity and include fixed effects for firm size, industry (2-digit SIC), firm age, and region. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.20: Propensity Score Matching: High Management Quality Across Technologies

	(1) Pr(AI=1)	(2) Pr(Cloud=1)	(3) Pr(Robotics=1)	(4) Pr(S. Software=1)	(5) Pr(S. Equipment=1)	(6) Pr(Other tech.=1)	(7) Pr(AI=1 | Other tech=0)	(8) Pr(AI=1 | Other tech=1)
ATET 2020	0.102**	0.035***	0.032	−0.004	−0.005	−0.004	0.087***	0.104***
	(2.05)	(3.22)	(0.53)	(−0.41)	(−0.34)	(−0.50)	(2.79)	(3.55)
Size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,039	6,091	1,587	5,668	4,012	6,640	2,008	1,886

Notes: This table reports average treatment effects on the treated (ATET) from propensity score matching, comparing firms with high management quality (top 50%) to those with low management quality across different technologies. Columns (1)-(6) examine AI, cloud computing, robotics, specialized software, specialized equipment, and any non-AI technology. Column (7) controls for general technology adoption; column (8) restricts the sample to firms that have adopted at least one other technology (Pr(AI=1 | ICT=1)). All specifications use nearest-neighbor matching with three neighbors and control for log labor productivity and fixed effects for firm size, industry (2-digit SIC), firm age, and region. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.21: Robustness to Winsorization

	(1) Pr(AI=1)	(2) Pr(AI=1)	(3) Pr(AI=1)	(4) Pr(AI=1)	(5) Pr(AI=1)	(6) Pr(AI=1)
Management Score 2020 (Winsor 1%)	0.265**					
	(3.07)					
Management Score 2020 (Winsor 5%)		0.268**				
		(2.86)				
Management Score 2020 (Winsor 10%)			0.291**			
			(2.82)			
Management Score 2020				0.261**	0.262**	0.262**
				(3.08)	(3.11)	(3.11)
Log Labour Productivity 2020	−0.019	−0.019	−0.019			
	(−1.26)	(−1.25)	(−1.25)			
Log Labour Prod. (Winsor 1%)				−0.017		
				(−0.95)		
Log Labour Prod. (Winsor 5%)					−0.019	
					(−0.93)	
Log Labour Prod. (Winsor 10%)						−0.022
						(−0.95)
Size FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,292	1,292	1,292	1,292	1,292	1,292
Adjusted R^2	0.024	0.024	0.024	0.023	0.023	0.023

Notes: This table examines robustness to winsorization of management scores and labour productivity. Columns (1)-(3) winsorize management scores at 1%, 5%, and 10% levels while keeping labour productivity unwinsorized. Columns (4)-(6) use unwinsorized management scores while winsorizing labour productivity at 1%, 5%, and 10% levels. All specifications include fixed effects for firm size, industry (2-digit SIC), firm age, and region. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.