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More than just plug and play: Early evidence on organisational 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 other technologies such as robotics, specialised equipment, or specialised software. We also find that management capabilities related to performance measurement appear particularly important to AI adoption. These results suggest that organisational complementarities are specific to different technologies, with implications for shaping policies to encourage AI adoption by firms.

1 Introduction

Artificial intelligence (AI) holds great promise for productivity and economic growth[1] (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[2] (Office for National Statistics, 2025). This gap in adoption rates has persisted, 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 emphasises organisational 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 organisational practices to generate value. However, the evidence on which organisational capabilities[3] matter for which technologies remains limited. It is an open question whether AI differs from other technologies, including prior generations of digital, in the specific requirements involved. Recent cross-country evidence documents a positive association between management practices and AI adoption at the aggregate level (Bick et al., 2026). Understanding which specific organisational capabilities matter, for which technologies, and why, however, requires deeper analysis at the firm level, which our paper provides.

This paper considers whether, compared to other technologies, early AI adoption is more reliant on organisational capital or particular aspects of organisational capital. We provide 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

[1] In some cases, cost-savings (Highfill and Samuels, 2026b,a).

[2] Additionally, Felten et al. (2024) find that AI adoption is concentrated among larger firms with Research and Development (R&D)-intensive operations and highly educated workforces. Calvino et al. (2026) also document that this concentration pattern is more pronounced for AI than for previous technologies, pointing to distinctive adoption barriers.

[3] We acknowledge that organisational capital, management practices, and management capabilities represent distinct concepts in different contexts. Organisational 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).

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, specialised equipment, or specialised software. Management scores also predict cloud computing adoption, though the effect is smaller, consistent with both technologies (AI and cloud computing) requiring ongoing organisational 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 organisational capabilities that enable firms to successfully adopt novel technologies in their early diffusion phase.

We also find that among the four measured components of structured 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 organisational complementarities differ for different technologies. Unlike industrial robots or manufacturing equipment, it is reasonable to hypothesize that AI systems will affect coordination and monitoring, and require adjustment of business processes. They produce outputs that need to be integrated into decision-making processes, and refined through iterative feedback. This organisational work is precisely what structured management practices enable.

Moreover, we find among firms that operate across multiple sites in the UK, those with decentralised product development are significantly more likely to adopt AI, even controlling for structured management practices. This hints that AI adoption may benefit from a decentralised decision-making structure for product development. Unlike robotics or specialised equipment, where investment decisions may 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 recognise where AI can add value, consistent with qualitative evidence collected through semi-structured interviews with UK businesses (Coyle et al., 2025), and conjecture 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 that largely addresses reverse causality concerns. We complement this with propensity score matching (and other matching approaches) to control for observed confounding factors. Our findings remain robust across multiple matching specifications. Importantly, the specificity of our results to AI rather than other technologies provides a powerful check against omitted variable bias. We are not simply capturing general firm quality or other potential unobserved correlates of both management and technology adoption. If well-managed firms were just better at everything, we might expect management scores to predict the use of all technologies. While we acknowledge our design cannot eliminate all sources of endogeneity, the combination of temporal ordering, matching methods, and technology-specific results lends some support to a causal interpretation. Moreover, establishing systematic associations between organisational capabilities and AI adoption provides valuable early evidence at a stage where firm-level empirical research on AI diffusion remains limited.

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, specialised software and specialised 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[4] 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 software and databases in 2021. 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. Temporal designs have shown that man-

[4]See table 4.

agement predicts the adoption of new technologies in response to economic shocks (Jones et al., 2024). Our temporal design establishes that management quality positively predicts subsequent AI 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 generative 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 organisational complementarities are technology-specific. The Bresnahan et al. (2002) framework emphasises that information technology investments require complementary organisational changes to generate productivity gains, but this literature has largely treated "IT" as a monolithic category. We show that different technologies make different organisational demands. AI adoption requires structured monitoring capabilities in ways that specialised softwares do not. This specificity has important implications for modelling technology adoption and productivity impacts.

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 decentralised product development, that predict adoption. Our results suggest that organisations 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, which might be more effective 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 LLMs. Our 2023-2024 data provide insights into adoption behaviour 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 organisational capabilities are also the binding constraint, then policies must address management practices and organisational readiness. Our findings suggest that different technologies will require different types of support.

2 Literature and theoretical motivation

Foundational research in both the management and economics literature on technology adoption has identified the factors that determine whether firms successfully implement new technologies, with the role of organisational capital in general a clear theme. We provide a short summary of determinants of ICT adoption in table 1.

Corrado et al. (2009) provides a now-standard framework for the comprehensive measurement and accounting of intangibles. Within this broad class of assets, organisational 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 organisational capital.

The seminal work by Brynjolfsson and Hitt (2000, 2003) found that productivity gains from ICT adoption only materialise when these investments are accompanied by complementary organisational changes, such as the restructuring of work processes and management practices. Bresnahan et al. (2002) formalised this insight, demonstrating that information technology, organisational 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. Building on this literature, Brynjolfsson et al. (2021) argue that general-purpose technologies exhibit a "productivity J-curve," where firms must invest in complementary organisational capital and restructuring before realising productivity gains. This suggests that organisational capabilities may determine not just the returns from technology but which firms adopt it in the first place.

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, organisational, and environmental

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
	Decentralisation	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

readiness within firms. Meanwhile, Oliveira et al. (2014) and Clohessy et al. (2018) demonstrated that existing technological and organisational capabilities determine adoption patterns by reducing integration costs, addressing governance challenges, and managing regulatory requirements. In terms of mechanisms, the literature finds that decentralisation facilitates adoption (Bresnahan et al., 2002), top management support drives implementation success (Faiz et al., 2024), and organisational slack enables innovation (Zhor, 2018).

In the management and information systems literature, foundational works such as Rogers's (2003) Diffusion of Innovations theory emphasised innovation characteristics (relative advantage, compatibility, complexity), adopter characteristics, and communication channels, while the Technology-Organisation-Environment framework (Tornatzky et al., 1990) highlights the technological context, organisational 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).

Academic work on ICT adoption finds that various forms of *intangible capital* are necessary complementary investments. Studies consistently find that firms with Research and Development (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 levels adopt ICT technologies faster (Svahn et al., 2017; Oliveira et al., 2014; Garrison et al., 2015; Byrd and Turner, 2001). Overall, the literature emphasises 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, organisational, 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) find widespread but shallow AI adoption. While 70% of firms in the US, UK, Germany, and Australia report using AI, most executives use it less than two hours per week, and over 80% report no productivity impacts. Felten et al. (2024) document that AI adoption is strongly associated with firm size, and intangibles such as R&D intensity and workforce skill composition, with adopters employing significantly more workers in cognitive occupations.

Consistent with the ICT adoption literature, digital infrastructure, organisational 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, organisational structure, and managerial capabilities predict AI 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 organisational 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 organisational 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 materialise because of the organisational 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 organisational 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 (the latter features in the 2023 sample only). The UK's MES data is in many ways comparable to data collected in the US's

Management and Organisational Practices Survey (USMOPS) and the German Management and Organisational Practices Survey (GMOPS).

The MES has hitherto been 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, and achieved a response rate of 27% (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 to achieve a panel stucture.[5] Removing firms that did not respond to questions on technology use leaves us with 7,525 valid respondents. Partial responses to the survey and other sample restrictions made for identification purposes gives us 1,292 respondents for our baseline regressions. We provide a summary of the data in table 2.

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
Plan to Adopt AI	Binary indicator equal to 1 if firm plans to adopt AI in 2024, 0 otherwise
Management Score	Overall management quality score (0–1), computed as average across all management practice items; higher values indicate better management
Log Labour 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

Continued on next page

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

Table 2 – continued

Variable	Definition
Data Intensity	Index (0–5) measuring breadth of data analytics practices used to support decision-making in 2023, where 0 = little to no analyses and 5 = uses all five types
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, developed in-house or purchased externally (£,000)
Panel C: Organisational Structure (MES)	
Multiple-Site Operation	Binary indicator equal to 1 if firm operates across multiple sites in the UK
Centralised Hiring	Binary indicator equal to 1 if hiring decisions are made only at headquarters; 0 if made at individual sites. Conditional on multiple-site operation
Centralised Product Development	Binary indicator equal to 1 if decisions to introduce new products or services are made only at headquarters; 0 if made at individual sites. Conditional on multiple-site operation
Centralised Investment	Binary indicator equal to 1 if a business site requires prior authorisation from headquarters for any capital asset purchase exceeding £1,000. Conditional on multiple-site operation
Panel D: Fixed Effects (FE)	
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

Continued on next page

Table 2 – continued

Variable	Definition
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 and data intensity are measured in 2020 to mitigate reverse causality concerns. Management sub-component scores are described in section 3.2.

3.1 Adoption of AI and other technologies

For the first time, the questionnaire for the 2023 wave of the MES[6] included a section that focused on the use of five different technologies: AI, cloud computing, robotics, specialised software, and specialised 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 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 otherwise. The average unweighted adoption rate of AI is 9% among UK businesses in 2023. In our main analysis we restrict our sample to include AI adopters and non-adopters who suggest that 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 organisational 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.[7] As such, it is important to

[6]This is the first instance where questions on AI adoption were included in an ONS survey. Subsequent to this survey, the Business Insights and Conditions Survey also included questions on AI adoption.

[7]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 behaviour or technological irrelevance.

note that our findings hold conditional on the technology being considered relevant and applicable by the firm.

Respondents were also asked to indicate whether they plan to adopt any of the five specified technologies in 2024. The ***binary indicator of plan to adopt AI*** 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.[8]

Table 3: Relative frequency distribution of technology use (merged 2020-2023 sample)

	AI	Cloud Computing	Robotics	S. Software	S. Machinery
Not applicable to business	50.0%	8.4%	64.9%	13.6%	32.2%
Applicable, not tested/used	18.5%	5.9%	12.6%	5.4%	6.0%
Tested but not used	9.2%	5.3%	2.5%	4.4%	3.7%
Used in processes/methods	8.6%	75.1%	8.5%	70.0%	47.4%
Don't know	13.6%	5.3%	11.4%	6.7%	10.7%
Total	100%	100%	100%	100%	100%

Notes: This table shows the relative frequency distribution of responses to technology adoption questions in the merged 2020-2023 MES panel sample. AI = Artificial Intelligence; S. Software = Specialised Software; S. Machinery = Specialised 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. We show the counts in table B.1.

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. For our sample, cloud computing stands out as the most widely adopted technology, used by three quarters of firms, while AI adoption remains relatively modest at 8.6%.

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

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

3.2 Measuring management practices and organisational 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.[9]

The ***overall management score*** is the average of 16 categorical questions (21 survey items) and ranges between 0 and 1.[10]

A management score closer to 1 indicates the responding firm continuously reviews their processes for improvement, conducts regular performance reviews, trains workers, employs and promotes based on merit (Office for National Statistics, 2024). We also examine ***subcomponent 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 organisational capital (Bloom and Van Reenen, 2007; Bloom et al., 2019). Previous studies reveal that management scores and their subcomponents 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 ***organisational structures*** in AI adoption. This is proxied as four binary variables: multiple-site operation; centralised hiring decisions; centralised product development; and centralised investment decisions. The multiple site operation variable is set to 1 if a respondent operates across multiple sites in the UK.

[9] *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.

[10] We calculate the 2020 overall management score slightly differently from the ONS, pending further exploration of the underlying data. 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 also been run with the original scores according to the ONS calculation to ensure consistency in results.

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. Centralised 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 centralised (set to 1) if a business site needs prior authorisation from their headquarters for any capital asset purchase over £1,000.

Because only businesses with multiple sites respond to questions about centralisation 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 organisational 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 labour productivity 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). In some specifications, we also control for data intensity,[11] measured as the number of data analytics types firms use (ranging from 0 to 5), to account for existing analytical capabilities.

3.4 Intangible capital

In some specifications, we control for other intangible capital investments, following the literature on complementarities between ICT and intangible assets (Brynjolfsson and Hitt, 2003; Bresnahan et al., 2002; Bloom et al., 2012). To achieve this, we link the panel MES 2020-2023 sample with two waves of the Annual Business Survey (ABS) in 2021 and 2022

[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).

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.

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 organisational capital (Bresnahan et al., 2002; Brynjolfsson and Hitt, 2000; Calvino and Fontanelli, 2026).

3.5 Descriptive statistics

Table 4 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), where the latter are restricted to firms where the technology is applicable. 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.[12]

AI adopters are recorded to have higher baseline management quality and higher labour productivity (£268,800 versus £193,500 per worker) in 2020. They also invest more heavily in complementary assets: brand spending in 2021, and software spending in 2021.

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

[12] Complete descriptive statistics for all variables are provided in Appendix Table B.2.

Table 4: Summary statistics

	All	AI Use = 1	AI Use = 0	Diff
Management score 2020	0.594	0.610	0.586	0.024
	(0.163)	(0.157)	(0.165)	
Labour productivity 2020 (£,000)	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)	
Centralised recruitment	0.430	0.384	0.455	-0.071
	(0.496)	(0.488)	(0.499)	
Centralised product development	0.605	0.561	0.628	-0.067
	(0.489)	(0.498)	(0.484)	
Centralised 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 no using AI in 2023. "Difference" reports the raw difference in means between the two groups (AI Use = 1 minus AI Use = 0). Labour productivity is value added per worker (£'000). Brand Spending 2021 and Software Spending 2021 are in £'000. Management score are measured in 2020. Multiple sites, Centralised recruitment, Centralised product development, and Centralised investment decision, and R&D 2021 are shares (means of binary indicators).
Source: Author's calculations, 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.

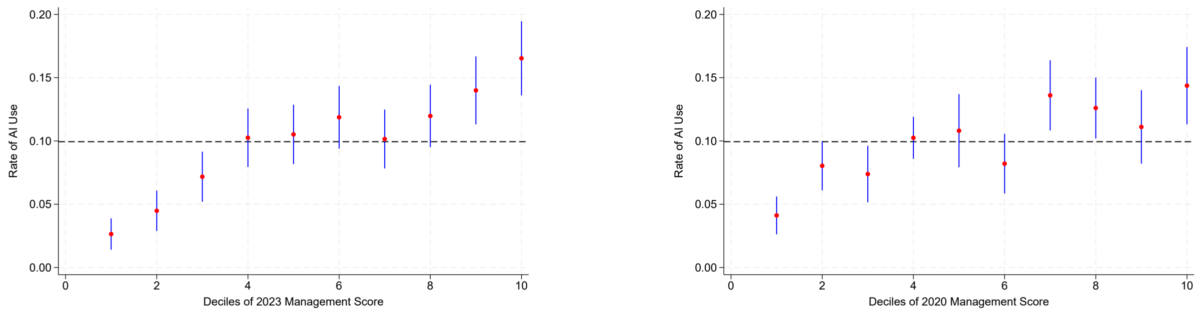
Table 5 presents conditional technology adoption rates from our matched panel sample. The table shows the percentage of firms using technology X (row) that also adopt technology Y (column). Reading across rows describes what technologies firms use *alongside* a given technology. Reading down columns shows what share of adopters of different technologies also use a particular technology.

For example, reading across the AI row, 93.3% of AI adopters also use cloud computing, Moreover, 18.1% of AI users also use robotics. Conversely, reading down the AI column, only 10.7% of firms adopting cloud computing and 18.3% of users of robotics technology also 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 specialised 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 specialised 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 B.3).

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. Firms in the highest management decile adopt AI at rates roughly 10 percentage points higher than those in the lowest decile. Similar

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 B.1.
Source: Authors' calculations, Office for National Statistics

patterns are evident in the full cross-sectional sample for 2023.

Overall, these patterns suggest that AI adoption is associated with better management 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 figures B.4 - B.3c). 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 is more reliant on organisational capital, or specific aspects of organisational capital, compared to other technologies. Our empirical approach exploits variation in management practices to test whether managerial capabilities are more important for AI adoption compared to other technologies. For our baseline specification, we estimate the linear probability model:

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

where $\text{Pr}(AI = 1)_{i,1}$ 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 structured management practices 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 labour 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 an 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, and, given our sample restrictions, conditional on AI being applicable at the firm.

To confirm whether AI adoption requires greater managerial 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, specialised software, and specialised equipment. We then compare the coefficient β_1^{AI}, against the coefficient from the regression with other technologies. Our null hypothesis that $\beta_1^{AI} = \beta_1^k$ for all technological assets k[13].

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 organisational structure characteristics (e.g., presence of

[13] k being cloud computing, robotics, specialised software, and specialised equipment

centralisation, decision-making authority), testing whether these structural features affect adoption conditional on the management score.

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.[14] 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 means of controlling for observables. This approach addresses potential concerns about functional form misspecification in our baseline linear probability 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.

[14]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).

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[15].

Our results also show that foreign ownership does not show a significant relationship 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 B.4) suggest that organisational capital may matter more for AI adoption among larger enterprises where implementation complexity is greatest.

[15]The result is also robust to broadening the adoption definition to include firms currently testing or piloting AI (See Appendix A)

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

	(1)	(2)	(3)	(4)	(5)	(6)
		Pr(AI = 1)			Pr(Plan AI = 1)	
Management Score 2020	0.242**	0.263**	0.267**	0.160**	0.139*	0.145*
	(2.68)	(3.06)	(3.06)	(2.68)	(2.03)	(2.13)
Log Labour Productivity 2020		-0.019	-0.018		0.019	0.022
		(-1.25)	(-1.14)		(1.15)	(1.23)
Foreign			-0.025			-0.039
			(-0.88)			(-1.28)
Observations	1292	1292	1292	881	881	881
Adj R2	0.023	0.024	0.023	0.017	0.017	0.017
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

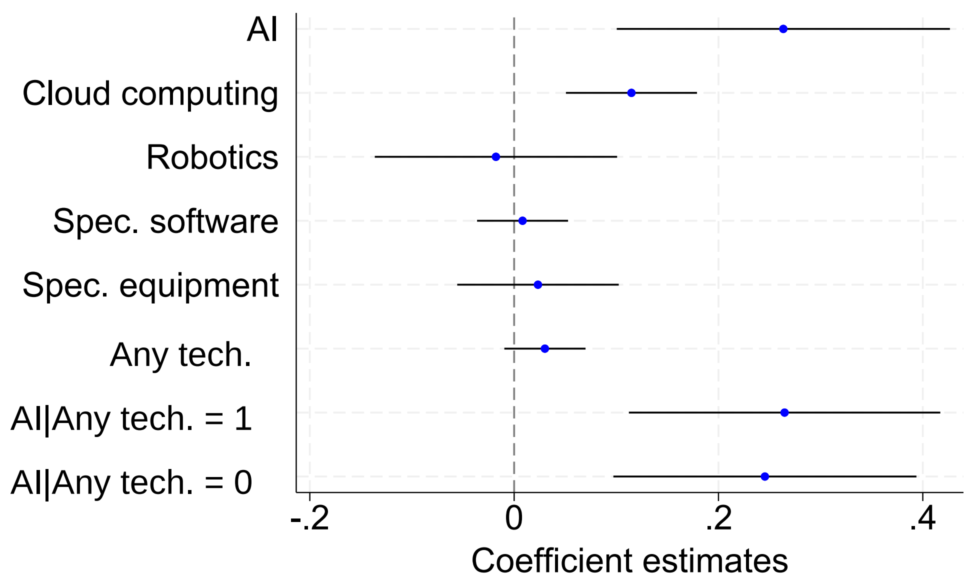
Note: This table reports the results from linear probability models estimating the likelihood of AI adoption (columns 1–3) and plans to adopt AI (columns 4–6). The dependent variable in columns 1–3 equals 1 if the firm has adopted AI technology, and 0 otherwise. The dependent variable in columns 4–6 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 organisational capital is required for the adoption of all ICTs. It is possible that our results do 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, specialised software, and specialised equipment. We also estimate whether management practices predict the probability of adopting at least one of these technologies.

We find no evidence that management practices significantly affect the adoption of robotics, specialised software, or specialised equipment (see figure 2). While management practices do predict cloud computing adoption, the coefficient magnitude is less than half that observed for AI. Also, the estimate for cloud computing is subject to potential re-

Figure 2: Effect of Management Practices on Technology Adoption



Notes: Coefficient estimates with 90% 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 labour productivity and include firm size, industry, age, and region fixed effects. Full regression tables in Appendix Table B.5.

verse causality. Cloud computing has been commercialised since 2002, prior to AI's much recent boom. Among MES respondents, 69% already use cloud computing systems and applications in 2023.

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 organisational characteristics specifically salient for AI implementation.

5.1 How management impacts AI adoption

To identify which aspects of structured management practices are associated with the probability of AI adoption, we run the same regression, but this time with the different components of the total management score.[16] 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 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

[16]Appendix Table C.3 replicates this analysis using contemporaneous 2023 management sub-component scores, where more sub-components are significant. This may reflect reverse causality, whereby AI adoption itself drives improvements in certain management practices. Though we cannot rule out other explanations.

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[17] by comparing the impact of each management practice component across different technologies. KPI tracking and target-setting exhibit much weaker and statistically insignificant relationships with robotics, specialised software, and specialised equipment adoption. For cloud computing, we observe moderate positive effects of monitoring practices, though central estimates are still smaller in magnitude than for AI.

Table 7: Which element of management impacts AI adoption?

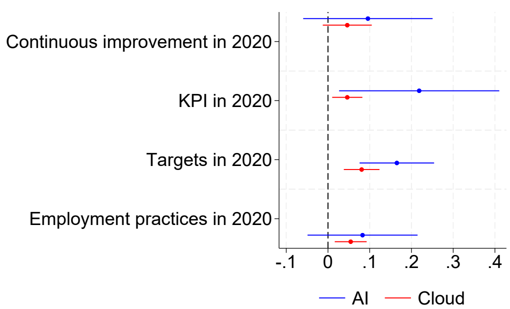
	(1)	(2)	(3)	(4)
		Pr(AI = 1)		
Continuous improvement in 2020	0.096			
	(1.17)			
KPI in 2020		0.219*		
		(2.16)		
Targets in 2020			0.165***	
			(3.50)	
Employment practices in 2020				0.083
				(1.19)
Log Labour Productivity 2020	-0.014	-0.016	-0.019	-0.015
	(-0.93)	(-1.02)	(-1.24)	(-0.95)
Observations	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

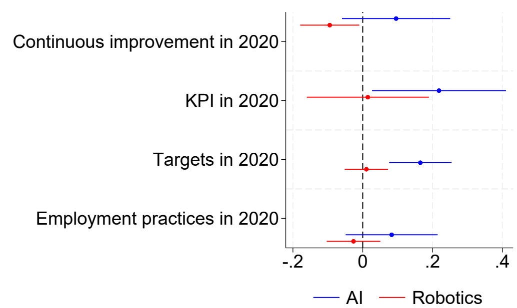
[17] See full results in Appendix tables B.6 and B.7

More specifically, KPI tracking and target setting can help address two problems with technology deployment in the presence of organisational 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 organisational '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.

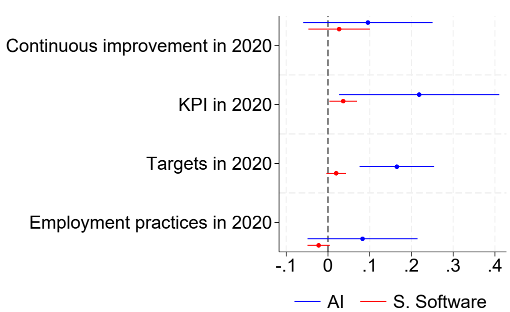
Figure 3: Which element of management impacts other technologies?



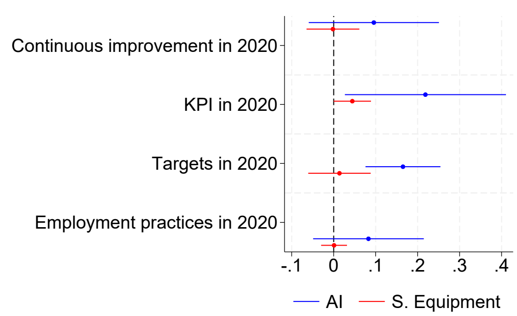
(a) Cloud Computing



(b) Robotics



(c) Specialise Software



(d) specialised 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) specialised software, and (d) specialised equipment. Points represent coefficient estimates, and horizontal lines show 90% confidence intervals. All regressions include controls for firm size, industry (2-digit SIC), firm age, region, and log labour 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 of data intensity, we find that our results still hold (see Appendix figure B.5 and table B.8), 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 organisational 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 - a specific 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.

Table 8: Organisational structures and AI adoption

	(1)	(2)	(3)	(4)
		Pr(AI = 1)		
Multiple sites	0.045			
	(1.53)			
Centralised recruitment		-0.052		
		(-1.25)		
Centralised product development			-0.056**	
			(-2.62)	
Centralised 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 Labour 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 organisational structure, looking at whether indicators of centralisation predict AI Adoption. The MES asks firms several questions on organisational structures, as discussed in section 3.2. Importantly, the centralisation questions are only asked of firms operating across multiple sites in the UK, as single-site firms do not face organisational decisions about whether to centralise or decentralise authority across locations. This reduces our sample size for the organisational structure analysis.

The results in table 8 imply that conditional on having the same management score and labour productivity, firms with more decentralised product development are more likely to adopt AI technologies. Specifically, firms where product development decisions are centralised exhibit a significantly lower probability of AI adoption, as shown by the negative and statistically significant coefficient on Centralised product development (column 3).

This pattern aligns with the idea that AI adoption benefits from a specific organisational 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, decentralised product development can proxy for broader organisational 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 decentralisation per se. In this case, the estimated relationship would reflect the underlying heterogeneity rather than a causal effect of decentralised decision-making.

We do not observe the same patterns for other technologies. For cloud computing (see table B.9), 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, centralised management systems, and real-time coordination across geographically dispersed locations. Meanwhile, we find that decentralised 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 centralisation and organisational structure show any statistically significant relationship with the adoption of specialised software (see table B.9). For specialised equipment, we find a marginally significant effect of decentralised recruitment, possibly because the skills required for operating specialised 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 organisational structure findings should not be interpreted as causal effects. Unobserved factors may simultaneously influence both centralisation decisions and technology adoption propensity. For example, exposure to intense competitive pressure might lead firms to both decentralise decision-making and adopt AI. Despite these identification limitations, our results provide valuable descriptive evidence on the organisational 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 (see Appendix tables C.1, C.2, C.3, and C.4). 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[18], we consistently find that high management quality significantly increases AI adoption probability (see Appendix table C.5).

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, specialised software, or specialised equipment, confirming that AI demands distinctive organisational capabilities (see Appendix table C.6). Finally, our results are not driven by outliers. Winsorizing management scores or labour productivity at various levels yields coefficients that remain statistically significant and consistent with our baseline estimates (Appendix table C.7).

6 Discussion

Our results suggest that the role of structured management practices, as organisational 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, specialised software, or specialised equipment adoption, suggesting use of AI is related to structured measurement of performance. Moreover, AI adoption is more likely for firms with decentralised product development. These findings have important implications for technology diffusion theory, organisational economics, and innovation policy.

Both Hoffreumon et al. (2024) and Challapally et al. (2025) suggested that even "ready-

[18] We apply propensity score matching, nearest-neighbour matching with one and three neighbours, and inverse probability weighting

made" AI tools still require significant internal development and customisation. Structured management practices reduce the organisational 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. 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 section 5.1). Tacitly, structurally managed firms might better anticipate and feel more confident tackling *ex-post* organisational 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 specialised 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 specialised 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 decentralised product development predicts AI adoption, although this is a tentative hypothesis. Technical teams working directly with business processes are better positioned to recognise where AI can add value. However, these bottom-up initiatives require management infrastructure to succeed. decentralised 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 AI is at very different points in their maturity compared to other technologies. For example, cloud computing is highly saturated with a 2023 adoption rate of around 70%, introducing a "ceiling effect" to our estimate. Moreover, 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.[19] 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.[20]

Our findings also extend and refine the organisational complementarities framework of Bresnahan et al. (2002). While Brynjolfsson and Hitt (2000) showed that IT demand depended on complementary organisational investments including decentralised 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 recognise that different technologies make different organisational demands.

This has implications for how to model technology adoption and diffusion. Standard adoption models emphasise 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 organisationally 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 and measurement of organisational capabilities may need refinement to understand

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

[20] 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.

the likely adoption path of AI (Coyle, 2026).

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 organisational costs of adopting an emerging technology under uncertainty, rather than the requirements for maintaining established technologies. Nevertheless, our results provide valuable insights into the organisational 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 organisational quality.

7 Policy implications

Our findings suggest that policies to accelerate AI diffusion should address organisational capabilities, rather than focusing solely on financial barriers or technical skills. Our results imply that management capability-building programmes should emphasise 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 organisational 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 organisational design for AI adoption or support for developing internal coordination mechanisms. Some studies have suggested that while a decentralised structure facilitates the initial adoption phase, centralisation 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 organisational changes are possible, AI adoption could generate higher synergistic pay-offs in non-modular organisations 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 organisational readiness. Blanket "technology adoption" policies that do not distinguish between technologies risk misallocating resources. Policymakers should assess what organisational capabilities each technology requires and target interventions accordingly.

8 Concluding remarks

If management practices are a binding constraint on AI adoption, as suggested by our results, then the AI adoption gap may reflect deeper organisational 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.

Our findings also provide evidence in support of efforts to measure intangibles more comprehensively in national accounts. If organisational capital is a meaningful predictor of AI adoption, then its omission from standard capital stock measures implies that official statistics may systematically understate the resources underpinning the digital transition. This points to a broader agenda for compilers of official statistics for the extension of asset boundaries to capture the organisational and managerial infrastructure that increasingly determines how economies absorb and benefit from general-purpose technologies such as AI.

What we present is a snapshot of the early adoption phase of AI, captured shortly after the mainstreaming of LLMs. Given the rapid pace of technological change, the patterns we document may evolve considerably as AI tools become more deeply embedded in firm workflows and as the frontier of capability continues to shift. Nonetheless, this provides an informative baseline against which future adoption trajectories can be measured. Understanding who adopted early, and why, is essential for interpreting the productivity and distributional consequences that follow. If organisational capital determined who was positioned to adopt at the frontier, it is likely to shape who benefits most as adoption diffuses more broadly across the economy.

Our findings open several directions for future research. First, we document which firms adopt AI but not how effectively they use it. Linking organisational capabilities to post-adoption productivity outcomes would reveal whether the management practices that facilitate adoption also determine the magnitude of AI's productivity effects. This presents a critical question for assessing AI's aggregate economic impact. Second, we measure adoption as a binary choice, but intensity and sophistication of use likely vary substantially across users of the technology. Understanding which organisational capabilities enable deeper AI integration remains an important research frontier. Third, as AI tools evolve, the organisational requirements for successful adoption may change. Whether improved user interfaces lower organisational barriers or whether more sophisticated applications raise them is an empirical question with significant policy implications. Finally, cross-country analysis would establish whether the patterns we document in the UK reflect universal features of AI as a general-purpose technology or are shaped by country-specific institutional and regulatory contexts. Such comparative work would inform whether policy interventions to strengthen organisational capabilities should be prioritized universally or tailored to national circumstances.

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A Comparing varying definitions of adoption

Table A.1: Changing the definition of adoption

	(1) Users vs Non-Users & NA	(2) Users & Testers vs Non-Users	(3) Users vs Testers
Management Score 2020	0.206***	0.340***	-0.146
	(4.51)	(3.91)	(-0.95)
Log Labour 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 compares AI 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source:* Authors' calculations, Office for National Statistics

Table A.2: 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 Labour 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.3: 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 Labour 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.4: Specialised 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 Labour 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 specialised software adoption across different user groups. Column (1) compares users to non-users and firms where specialised 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.5: Specialised 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 Labour 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 specialised equipment adoption across different user groups. Column (1) compares users to non-users and firms where specialised 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.1 Additional results

Table B.1: 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 = Specialised Software; S. Machinery = Specialised 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.

Table B.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
	(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)				

Continued on next page

Table B.2 – Continued from previous page

	All	AI Use = 1	AI Use = 0	Difference
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)	

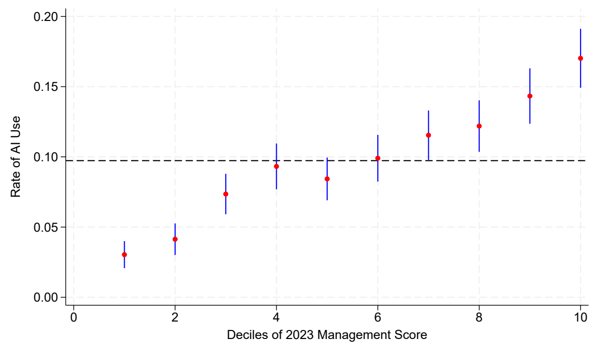
Notes: This table presents descriptive statistics for the full sample and by AI adoption status. For continuous variables, means are reported with standard deviations in parentheses. For binary and categorical variables, proportions are reported with standard deviations in parentheses. The Difference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

Table B.3: Conditional technology adoption rates, UK firms 2023

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

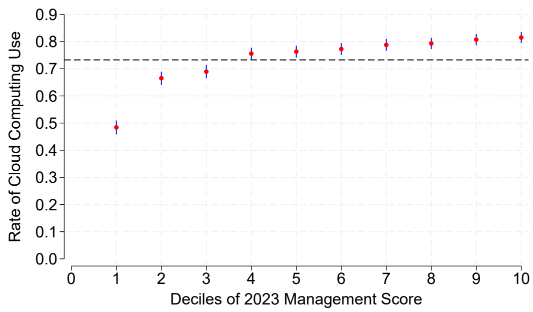
Source: Office for National Statistics, Business Insights and Conditions Survey (BICS), 2023.
Notes: Table shows the percentage of firms using technology X (row) that also use technology Y (column). For example, 91% of AI adopters also use cloud computing, while 11% of cloud adopters use AI..

Figure B.1: Management Score 2023, Full Sample

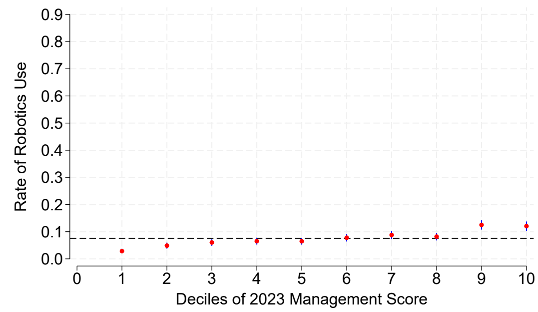


Note: Figure shows AI adoption rates across deciles of the management score distribution for the full sample in 2023. The horizontal dashed line indicates the overall AI adoption rate for the panel sample. Management scores are calculated from the Management and Expectations Survey (MES). Higher deciles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

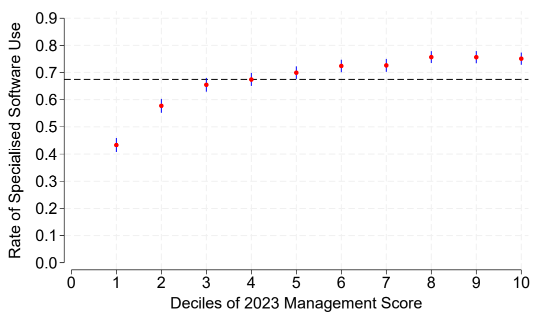
Figure B.2: Technology Adoption and 2023 Management Score, Full Sample



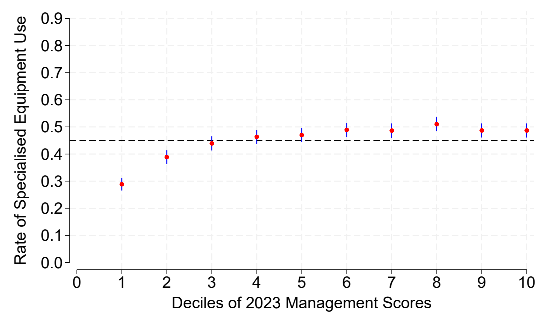
(a) Cloud Computing Adoption Rates



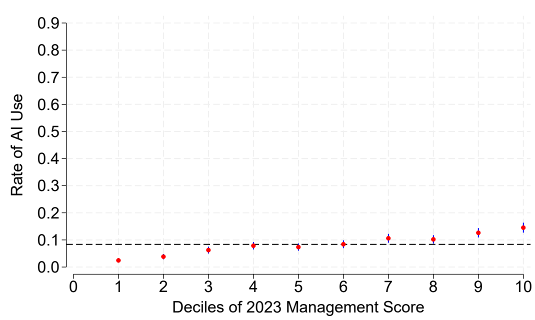
(b) Robotics Adoption Rates



(c) specialised Software Adoption Rates



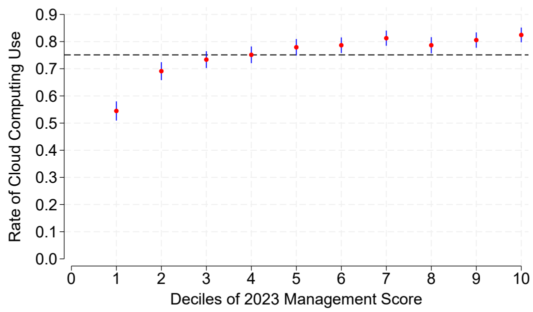
(d) specialised Equipment Adoption Rates



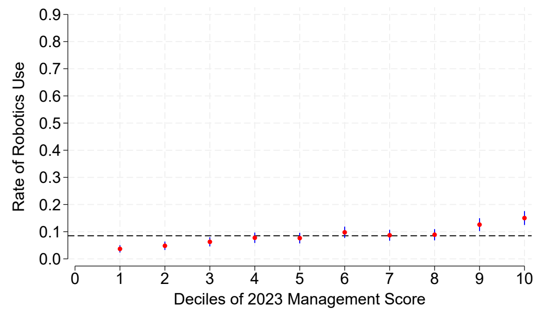
(e) AI Adoption Rates

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) specialised software, (d) specialised 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 90% confidence intervals. The horizontal dashed line indicates the overall adoption rate for each technology across the sample.
Source: Authors' calculations, Office for National Statistics.

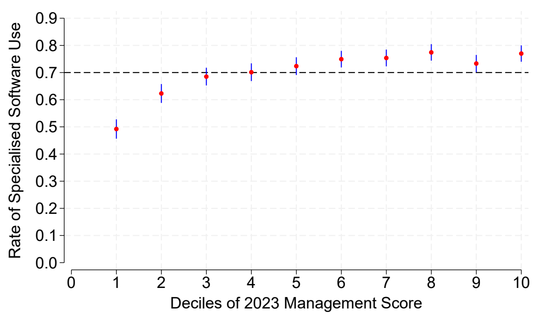
Figure B.3: Technology Adoption and 2023 Management Score, Merged Data 2020−2023



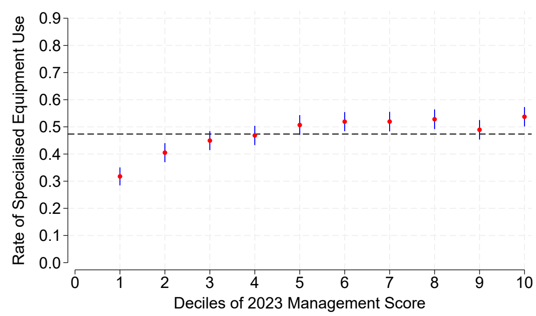
(a) Cloud Computing Adoption Rates



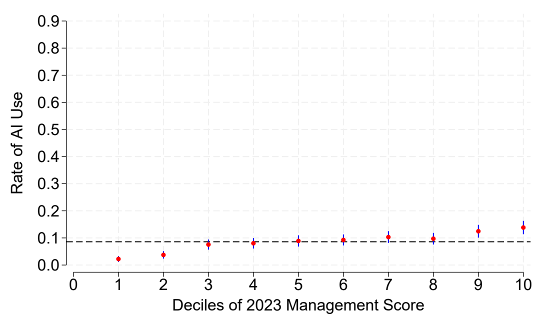
(b) Robotics Adoption Rates



(c) specialised Software Adoption Rates



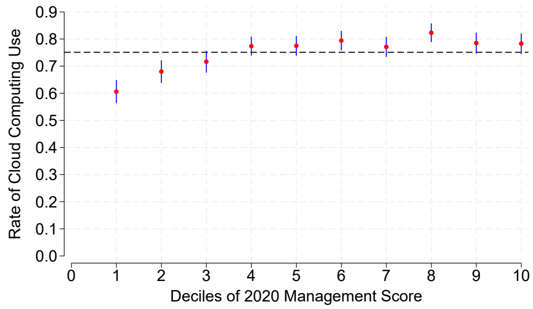
(d) specialised Equipment Adoption Rates



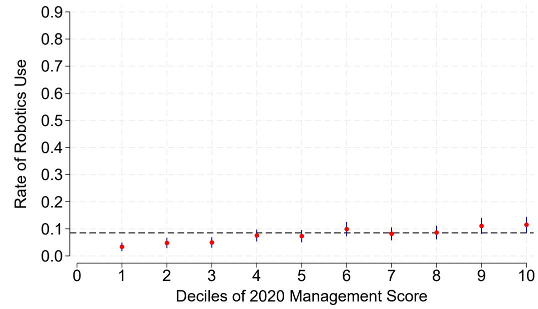
(e) AI Adoption Rates

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) specialised software, (d) specialised 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 90% confidence intervals. The horizontal dashed line indicates the overall adoption rate for each technology across the sample.
Source: Authors' calculations, Office for National Statistics.

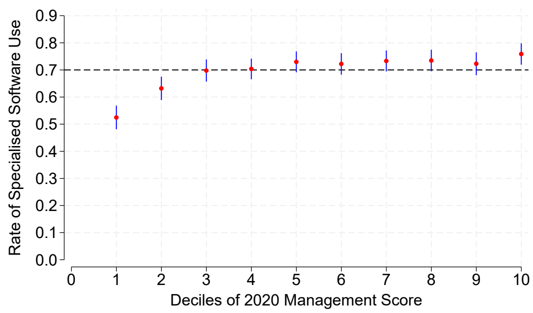
Figure B.4: Technology Adoption and 2020 Management Score, Merged Data 2020−2023



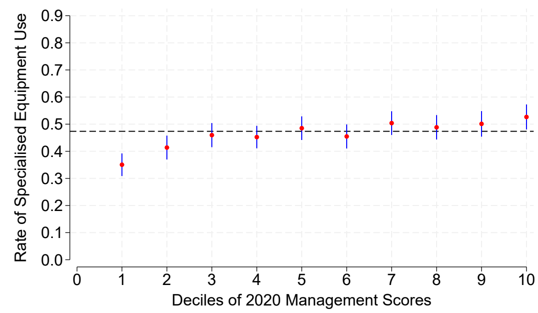
(a) Cloud Computing Adoption Rates



(b) Robotics Adoption Rates



(c) specialised Software Adoption Rates



(d) specialised 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) specialised software, (d) specialised 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 90% 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 B.4: 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 Labour 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 B.5: 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 Labour 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, specialised software, specialised 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 B.6: 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)		
Targets subscore in 2020			0.0807***				0.0104	
			(0.0226)				(0.0328)	
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

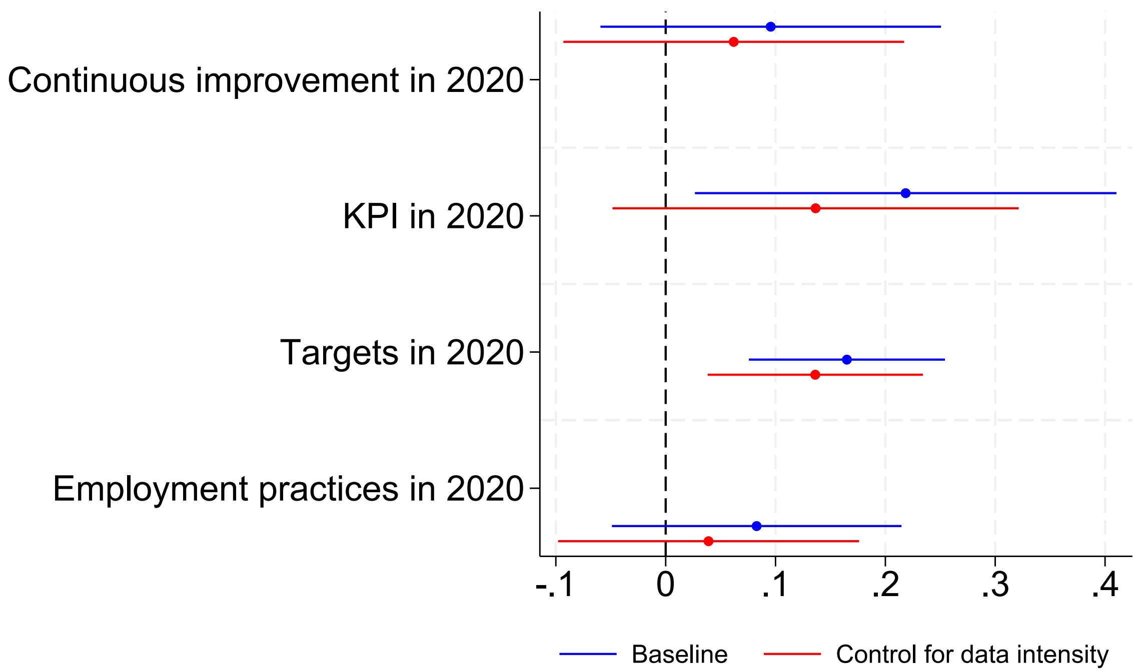
Note: This table reports the results from linear probability models estimating the likelihood of cloud computing adoption (columns 1-4) and robotics adoption (columns 5-8). The dependent variable in columns 1-4 equals 1 if the firm has adopted cloud computing, and 0 otherwise. The dependent variable 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 B.7: Which element of management impacts specialised 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)		
Targets subscore in 2020			0.0197				0.0137	
			(0.0124)				(0.0393)	
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 specialised software adoption (columns 1-4) and specialised equipment adoption (columns 5-8). The dependent variable in columns 1-4 equals 1 if the firm has adopted specialised software, and 0 otherwise. The dependent variable in columns 5-8 equals 1 if the firm has adopted specialised 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

Figure B.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 B.8.
Source: Authors' calculations, Office for National Statistics

Table B.8: 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 B.9: 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)			
Centralised recruitment		-0.0116				-0.105		
		(0.0214)				(0.0795)		
Centralised product development			-0.00592				-0.0791*	
			(0.0140)				(0.0394)	
Centralised investment decision				0.0212				-0.000402
				(0.0203)				(0.0562)
Log Labour 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 B.10: Organisational structures and technology adoption: Specialised 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)			
Centralised recruitment		-0.00491				-0.0246*		
		(0.0120)				(0.0128)		
Centralised product development			-0.0100				-0.0128	
			(0.00836)				(0.0118)	
Centralised investment decision				0.0184				0.0236
				(0.0246)				(0.0263)
Log Labour 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 specialised software adoption (columns 1-4) and specialised equipment adoption (columns 5-8). The dependent variable in columns 1-4 equals 1 if the firm has adopted specialised software, and 0 otherwise. The dependent variable in columns 5-8 equals 1 if the firm has adopted specialised 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

C.1 Robustness checks

Table C.1: Adopt AI and management practices

	(1) Pr(AI=1)	(2) Pr(AI=1)	(3) Pr(AI=1)
Management Score 2023	0.288***	0.292***	0.297***
	(3.62)	(3.66)	(3.63)
Log Labour Productivity 2023		-0.003	-0.002
		(-1.10)	(-0.63)
Foreign Ownership			-0.029**
			(-2.53)
Constant	0.081	0.093	0.087
	(1.61)	(1.82)	(1.61)
Size FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	2,495	2,495	2,495
Adjusted R^2	0.019	0.018	0.018

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 C.2: Plans to adopt AI and management practices

	(1) Pr(Plan AI=1)	(2) Pr(Plan AI=1)	(3) Pr(Plan AI=1)
Management Score 2023	0.288***	0.292***	0.297***
	(3.62)	(3.66)	(3.63)
Log Labour Productivity 2023		-0.003	-0.002
		(-1.10)	(-0.63)
Foreign Ownership			-0.029**
			(-2.53)
Constant	0.081	0.093	0.087
	(1.61)	(1.82)	(1.61)
Size FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	2,495	2,495	2,495
Adjusted R^2	0.019	0.018	0.018

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 C.3: 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 Labour 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 C.4: Organisational 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)				
Centralised Recruitment		-0.018			0.011
		(-0.69)			(0.31)
Centralised Product Dev.			-0.043**		-0.101*
			(-2.60)		(-2.24)
Centralised 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 Labour 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 organisational structure affects AI adoption. Multiple Sites is a binary indicator for firms with multiple locations. Centralised variables indicate whether decisions about recruitment, product development, or investment are made centrally (vs. decentralised to individual sites). Column (5) includes all organisational structure variables simultaneously. Sample sizes vary because organisational 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 C.5: 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 C.6: 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, specialised software, specialised 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 labour 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 C.7: 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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