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What drives UK firms to adopt AI and robotics, and what are the consequences for jobs?

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Abstract

Many studies emphasise the potential for widespread job displacement from exposure to AI technologies. Fewer studies also examine the actual impact on job creation, as well as skills demand, and the quality of jobs. Since AI may have multiple positive and negative consequences, it is important to know what drives outcomes, and which factors moderate its impact.

Drawing upon theories of technology adoption, we present an empirical study of factors influencing decision-maker perceptions of AI, which we hypothesise mediate organisation and environmental factors and adoption.

We theorise two moderators for the impact of AI on net job creation, skills demand, and job quality. First, Regional Innovation Readiness reflects the availability of enabling resources in the local environment, in the form of an educated workforce and the connectivity infrastructure. Second, High Involvement HRM is an investment orientation which includes employees in the process of adoption.

We test our hypotheses using primary data collected from 1012 organisations across all sectors of the UK economy. We find both Regional Innovation Readiness and High Involvement HRM play a significant role in influencing positive and negative outcomes from AI adoption. We discuss the significant implications for policymakers as well as managers.

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1. Introduction

Dramatic, speculative headlines about artificial intelligence (AI) and autonomous robots have occupied the media with increasing frequency. A significant subset of these stories focuses on the question of whether AI and AI-enabled hardware will eliminate a large number of jobs, magnifying existing socio-economic inequalities While the focus has been on impacts of AI on the labour market (e.g., Acemoglu & Restrepo, 2020; Brynjolfsson et al., 2018; Dauth et al., 2017; Georgieff & Milanez, 2021; Lassébie & Quintini, 2022), significantly less research addresses firm-level impacts on job creation as well as displacement, on skills demand, and crucially, on the quality of jobs (Acemoglu & Lelarge, 2020; Acemoglu & Restrepo, 2020; Holm & Lorenz, 2022; OECD, 2023). AI can automate many tasks and substitute human labour, but equally it may augment and complement human capabilities, enabling workers to delegate the most routine and boring work to machines and spend time on interesting, challenging, meaningful, and value-creating work (Bankins & Formosa, 2023; Brynjolffson & McAfee, 2014; Lane et al., 2023; Milanez, 2023). A significant question to be addressed is what influences AI adoption, and what causes different work outcomes as a result of their adoption. For example, do firms adopt AI after consultation with their workers to enhance work quality and get more productivity out of their existing employees, possibly increasing job creation as well, or do they aim to get more productivity by replacing workers with faster and more efficient machines?

Most studies estimating AI's impact offer judgments of the technical feasibility or future probabilities of job or task automation, by comparing what is currently done by labour with what machines can do (e.g., Arntz et al., 2016; Felten et al., 2018; Frey & Osborne, 2017; Lassébie & Quintini, 2022). However, significant variations between countries, institutional contexts, and organisations influence the rate of technology adoption and its subsequent impacts on jobs and work (e.g., Barley, 2020; Kapetaniou & Pissarides, 2023; Thomas, 1994). To better understand this issue, we must look within organisations to understand the processes and outcomes of AI adoption (Holm & Lorenz, 2022; Raj & Seamans, 2019). While often treated as objective, the meaning of technology is socially constructed (e.g., Barley, 2020; Orlikowski, 2009), and its attractiveness for adopters is subjective and context-dependent (Downs & Mohr, 1976; Rogers, 2010). This implies that the impacts of technology on work are not predetermined by objective characteristics of the technology but are subject to socially situated cognitions of decision-makers and stakeholders involved in adoption and implementation (Orlikowski, 2009). To promote positive outcomes and mitigate negative implications of AI-based automation, it is valuable to understand how decision-makers' perceptions of technology influence the creation or elimination of jobs, skills requirements, and overall job quality. We need to understand the contingencies influencing management choices with respect to AI and jobs.

This study addresses these gaps by making four contributions. First, we address the call for more studies of the impacts of AI at the level of the organisation (e.g., Holm & Lorenz, 2022; Raj & Seamans, 2019). Rather than treating AI as a homogenous technology with fixed, objective characteristics (Downs & Mohr, 1978), we adopt a process perspective in which subjective perceptions of the technology and its benefits are central. We include AI that is deployed to perform cognitive tasks and to control autonomous hardware and robotics in order to automate physical tasks. Extending prior work on technology acceptance, we treat perceptions of technology as mediating the relationship between organisational and environmental factors and the adoption of AI and robotic technologies. We identify those factors which influence diversity in perceptions of the utility and fit of AI within organisations and provide empirical support for the mediating role of these perceptions with respect to adoption. This addresses past criticism of technology adoption studies that the characteristics of technology are not fixed, but are subjective and context-dependent (e.g., Downs & Mohr, 1978; Orlikowski, 2009).

Our second contribution is to provide evidence of the significance of context as an enabling factor in the influence of AI on jobs and job quality. The study provides robust evidence that even within a national economy, differences between regions in educational investments, the availability of an educated workforce, and connectivity infrastructure play an important role. We demonstrate that variations in innovation readiness across UK regions significantly alter the relationship between technology adoption and work outcomes, with high levels of readiness being associated with more positive outcomes. This supports the long-standing hypothesis that workforce preparedness influences technology adoption and diffusion (Goldin & Katz, 2008). This finding has major policy implications for national and regional industrial and educational strategies.

The third contribution of this study is to provide evidence for the role of HRM practices in AI adoption and its impacts on work outcomes. This study shows that an investment-focused HRM philosophy, with high-involvement practices, promotes adoption through the mechanism of decision-makers' perceptions about AI. HRM practices contribute to technology adoption through their influence on the identification, understanding, and perceived benefits of AI. At the same time, we provide evidence that HRM philosophy and practices positively moderate the impact of AI adoption on jobs and work quality by altering incentives with respect to augmentation versus substitution of labour.

Finally, this study goes beyond the question of the number of jobs being disrupted to include consideration of job quality. We define job quality in terms of multiple dimensions of 'good work': fair pay, reasonable hours, work that is interesting, challenging, and meaningful, opportunities for personal growth and development, and the ability to have a say about issues in the workplace which affect you (e.g., Cazes et al., 2015; Osterman, 2013; Warhurst, Wright & Lyonette, 2017). If the quality of remaining jobs is diminished, or new jobs are created which are of worse quality, then this would be to the detriment of employees, and society (Georgieff & Milanez, 2021; Taylor et al., 2017). The impact on job quality is potentially significant, yet existing empirical evidence is limited (OECD, 2023).
In summary, in this paper, we challenge the question of technological determinism of AI with respect to jobs, skills and job quality by exploring how both context and management choices moderate its impact on work outcomes. We next develop our hypotheses, drawing on existing literature on technology adoption, and on the impacts of technology. We then describe our empirical study which examines the hypothesised relationships using recently collected survey data and secondary data from the UK. After presenting our results, we discuss the significance of the study for policy and practice, as well as for future research in the conclusion of the paper.

2. Literature Review

2.1 Technology adoption

Technology adoption is not a single decision but in fact involves multiple stages. Rogers (2010) suggests that innovation adoption involves five stages, while other models suggest two or three identifiable stages (Damanpour & Schneider, 2006; Gopalakrishnan & Damanpour, 1997; Zmud, 1982). In general, there is an initiation stage, which involves becoming aware of an innovation, forming an attitude towards that innovation itself, or its potential applications (Moore & Benbasat, 1991), and the evaluation of the technology leading to the initial adoption decision. Adoption is followed by implementation, which includes technology trials followed by sustained implementation (Gopalakrishnan & Damanpour, 1997; Meyer & Goes, 1988). There has been a tendency to focus on the decision to adopt, and less attention to implementation or its consequences (Bailey & Barley, 2020; Tornatzky & Klein, 1982). Few studies have examined processes preceding, or impacts after adoption (Bailey & Barley, 2020; Meyer & Goes, 1988).

Diffusion of innovations

Perhaps the most widely known framework is the 'diffusion of innovations' (DOI) perspective. Rogers (2010) identifies five characteristics of an innovation which impact its rate of diffusion. First, the relative advantage of the new technology over existing tools and methods. Second, the compatibility of the new technology with existing norms, culture, values, and needs of potential adopters. Third, the perceived complexity of the technology with respect to existing knowledge and abilities. Fourth, the observability or transparency of the workings of the technology. Fifth, the trialability or opportunity to test and experiment prior to choosing to adopt a given technology. These five have been identified across a wide range of contexts, in international settings, although they are rarely included simultaneously in individual studies (Tornatzky & Klein, 1982).

Despite its broad foundations (Rogers, 2010), the DOI literature has been criticised on several fronts. First, for a general instability in results (Damanpour, 1987; Dewar & Dutton, 1986; Downs & Mohr, 1976; Meyer & Goes, 1988; Zmud, 1982). One reason for this is that the salient attributes of innovations are perceptual and subjective rather than objective (Downs & Mohr, 1976). The perceived relative advantage, compatibility and complexity of a new technology are not fixed or stable but will vary across individuals, organisations, contexts, and time. A second source of instability is inconsistent support for all five factors. In their meta-analysis, Tornatzky and Klein (1982) only find consistent support for relative advantage, compatibility, and complexity.

A third criticism of the DOI perspective is that it focuses primarily on early adopters, rather than across populations of adopters and potential adopters. Variations in institutional environments, and the availability of complementary resources such as human capital and access to suitable information and communications technologies, can be expected to impact the ability or willingness to adopt AI. Building on this perspective, and considering these criticisms, we place perceptions of technology, in terms of relative advantage, compatibility and complexity, at the heart of our conceptual framework (Figure 1).

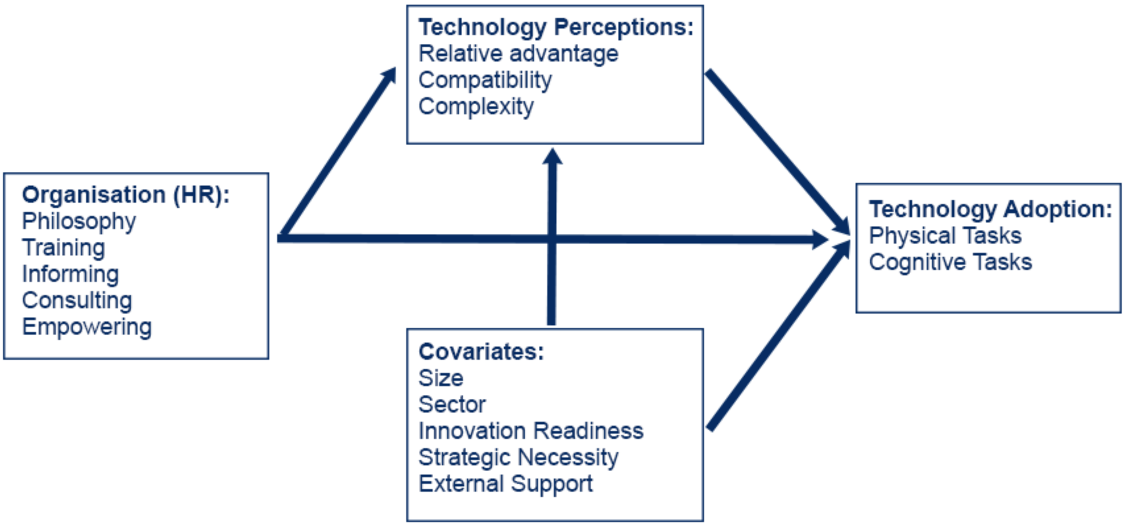


Figure 1

The Technology Acceptance Model

Within the information systems field, the question of whether and why users will adopt a given technology has led to a theoretical framework grounded in the theory of reasoned action and the theory of planned behaviour (Davis, 1989; Fishbein & Ajzen, 1975; Lederer et al., 2000; Porter & Donthu, 2006). This 'Technology Acceptance Model' (TAM) suggests that adoption is influenced by beliefs about the desirability and feasibility of the new technology. Desirability reflects the perceived usefulness, or whether individuals perceive that a given technology will help them perform their job better, which is consistent with the concept of relative advantage (Moore & Benbasat, 1991; Rogers, 2010). Feasibility judgments reflect both the perceived complexity/ease of use of the new technology and perceived compatibility with current operations. Thus, the TAM represents an evolution of the DOI perspective, in that it identifies similar core variables, but because TAM is based on the theory of reasoned action, it explicitly links to individual cognitions and intentions as predictors of adoption behaviour (Lederer et al., 2000; Porter & Donthu, 2006).

Studies have applied the TAM to a variety of digital technologies, from computer hardware (e.g., Igbaria et al., 1995), automated technologies (Haynes & Thies, 1991), the internet (Morris & Dillon, 1997; Teo, Lim & Lai, 1999; Porter & Donthu, 2006), email (e.g., Adams, Nelson & Todd, 1992; Gefen & Straub, 1997; Straub et al., 1995), and a wide a variety of software (Adams et al., 1992; Davis, 1989; Davis et al., 1989; Hendrickson & Collins, 1996; Mathieson, 1991). Overall, it has been broadly established that individual adoption decisions are influenced by perceptions of the useability and usefulness of the technology. As such, the TAM overcomes some criticisms of the diffusion of innovations approach by explicitly focusing on the subjective perceptions of technologies as opposed to their objective characteristics. This leads to our first hypothesis:

H1: *Perceptions of the relative advantage, complexity, and compatibility of AI and robotic automation technology are positively associated with their adoption by organisations.*

The Technology Organisation Environment

Implicit in the TAM is the fact that context matters for technology perceptions. In recognition of this, some studies have included environmental factors in addition to technology perceptions and organisational factors. The so-called Technology-Organisation-Environment (TOE) framework differs from the TAM in that the focus is explicitly organisational versus individual. From this perspective, cognitions concerning value, the ease of use of a technology (complexity), and perceived compatibility are framed relative to organisational, rather than individual, capabilities. This includes having sufficient financial resources to be able to afford the new technology in terms of initial installation and perceived future development or running costs. It also includes having the technological sophistication to support the management and use of the new technology.

2.2 Human Resource Management and Technology Perceptions

HRM practices are an important source of adoption-related capabilities, since they drive the development of the human and social capital needed for technology adoption and implementation (e.g., Hayton, 2003; 2005). We focus on a subset of those practices which we believe are most relevant to the technology perceptions at the centre of our conceptual model: training, information sharing, consulting with employees about technology, and empowerment.

Skill demands are a central question in the automation of work. When tasks are automated, it is the lower skill tasks which are removed first. Average skill level required increases following automation, because proportionally more time is spent on higher skill-demand tasks (Thomas, 1994). A second reason skill requirements increase with automation is that when there are failures, the cost of detection and repair can be greater than for non-automated approaches and this demands a higher average skill level (Adler & Borys, 1989). AI-based technologies, being highly flexible and rapidly adaptable and updateable, will be associated with very high rates of organisational change and innovation, and consequently demand significant adaptability and flexibility from employees, once again raising skill demands.

A further consideration with respect to skill levels and AI is that of implementation spirals: the initial adoption of a technology, for example Robotic Process Automation (RPA), leads to demand for the development of complementary capabilities with respect to data integration which in turn make adoption of further technologies both easier and more likely (Adler & Borys, 1989; Felten et al., 2018). It follows that, from the perspective of AI adoption, the most significant resources are human resources (Adler & Borys, 1989; Dewar & Dutton, 1986; Thomas, 1994). This suggests that investments in training will enhance the perceived relative advantage, ease of use, and compatibility of AI.

There is a long-standing body of research on the role played by various forms of employee involvement and voice (e.g., Morrison, 2011). Employee involvement may range from two-way information sharing between employer and employees, to employee empowerment in day-to-day decision-making related to their work, through to consultation in the strategic direction of the organisation. Employee involvement is considered to be a central element of a sociotechnical systems approach to organising, which emphasises the benefits of worker-management collaboration in the adoption of new process technologies (Trist, 1980). Employee involvement is frequently present in high-performance, high-commitment, or high-involvement work systems (e.g., Huselid, 1995; MacDuffie, 1995), and a comprehensive meta-analysis of employee participation reports significant positive effects on productivity (Doucouliagos, 1995).

Employee involvement has a positive impact on discretionary contributions, organisational learning, and employee flexibility, each of which is expected to enhance the perceptions of technology via better awareness, understanding, and complementarity (Arthur, 1994; Bartel et al., 2005; MacDuffie, 1995). Employee discretionary contributions include the identification of new technological solutions for the improvement of work processes, and a willingness to engage in the experimentation and development of new work processes which increase the likelihood of successful adoption (e.g., Hayton, 2003; Thomas, 1994). Empowerment is expected to enhance the identification and adoption of technology through its influence on perceived attributes of technology: increasing the perceived benefits, reducing perceived complexity, and enhancing perceived compatibility, which in turn leads to greater propensity to adopt new AI technologies.

A systems view of HRM (e.g., Huselid, 1995) suggests that the benefits from any one HRM practice, such as information sharing, are reinforced by the simultaneous implementation of other supportive management practices such as employee consultation and skills development. To the extent that a particular practice, such as training, is consistent with other human resource practices, and work organisation, there will be a synergistic impact on outcomes (Arthur, 1994; MacDuffie, 1995). From the perspective of the adoption of AI, we propose there are four particularly salient HRM and complementary practices: investments in training; information sharing; employee consultation; and employee empowerment. In general, although not conducted with AI as the focal technology, prior studies have demonstrated that high involvement HR philosophy and management is supportive of the implementation of advanced process technologies (MacDuffie, 1995). Similarly, evidence has demonstrated that it is when combined with more sophisticated management practices, organisations obtain higher returns from investments in advanced information technologies (Bartel et al., 2005; see also Bloom et al., 2012a). In sum, a human-centred approach to new technology introduction, which includes two-way information sharing, employee participation in decision-making, and the promotion of worker voice, can be expected to enhance organisational readiness. That enhanced readiness influences the perceived attractiveness of AI technologies. This leads to our second and third hypotheses:

H2: *High-involvement HRM will be positively associated with favourable perceptions of AI technologies.*

H3: *Technology perceptions will mediate the association between high-involvement HRM and the adoption of AI technologies.*

Organisational sitze is expected to be associated with AI adoption (e.g., Autor, Salomons & Seegmiller, 2023; OECD, 2023). One reason organisational size is associated with the adoption of innovations is because it proxies the availability of human capital within the firm (Dewar & Dutton, 1986). There is strong evidence that smaller firms are less likely to adopt technology of all kinds (e.g., Berger et al., 2021). Smaller firms tend to have greater CEO centralisation, which narrows the range of information processing by decision-makers, and consequently inhibits innovation (Damanpour, 1991; Damanpour & Schneider, 2006). Smaller organisations also tend to employ more generalists and fewer technical specialists, inhibiting their capacity for identifying, evaluating, and implementing new technologies (Thong, 1999). Smaller firms also tend to lack the financial resources necessary for the investigation, experimentation, development, and utilisation of new technologies (Berger et al., 2021; Damanpour, 1991; George, 2005; Thong, 1999). Innovation of all types tends to benefit from a long-term orientation, and yet smaller firms often face financial constraints, forcing them to prioritise short-term objectives. Thus, multiple factors associated with size may inhibit technology adoption by small firms, and this is supported in numerous studies of information systems technology adoption (Chwelos, Benbasat & Dexter, 2001; Iacovou et al., 1995; Kuan & Chau, 2001). In sum, there appear to be systematic differences between large and small firms in the adoption of information technologies (Waldman-Brown, 2020) which we might expect to extend to AI-based technologies.

H4a: *Organisational size will be positively associated with favourable perceptions of technology.*

H4b: *Organisational size will be positively associated with AI technology adoption.*

As an extension to the TAM, the TOE framework explicitly incorporates external environmental considerations (e.g., product market competition; needs of customers or trading partners) as potential influences on adoption decisions. Previous studies show that pressures from trading partners and external competition positively impact the willingness to adopt EDI among SMEs (Chwelos et al., 2001; Iacovou et al., 1995; Kuan & Chau, 2001; Waldman-Brown, 2020). Waldman-Brown (2020) identifies two types of outside forces: First, when a new technology can pay for itself in the context of a single 'anchor' contract. Second, where a new technology offers improvement demanded by exogenous pressures such as cost competition. These observations lead us to expect that perceived pressure from customers, or the belief that key competitors are adopting AI technologies to their advantage, will be influential upon perceptions of the potential benefits of the technology, increasing attractiveness.

External factors are not only negative, the presence of supportive external institutions such as trade associations (Inkpen & Tsang, 2005) and universities (Vick & Robertson, 2017) are influential upon the processes of knowledge transfer expected to support technology adoption. External institutions offer the opportunity for collaboration, knowledge exchange through social networks, training, and more generally as sources of knowledge and support for technology adoption. Greater awareness and understanding enhance the perceived benefits of AI, reducing perceived complexity, and enhancing perceived compatibility. These considerations suggest the following additional hypotheses.

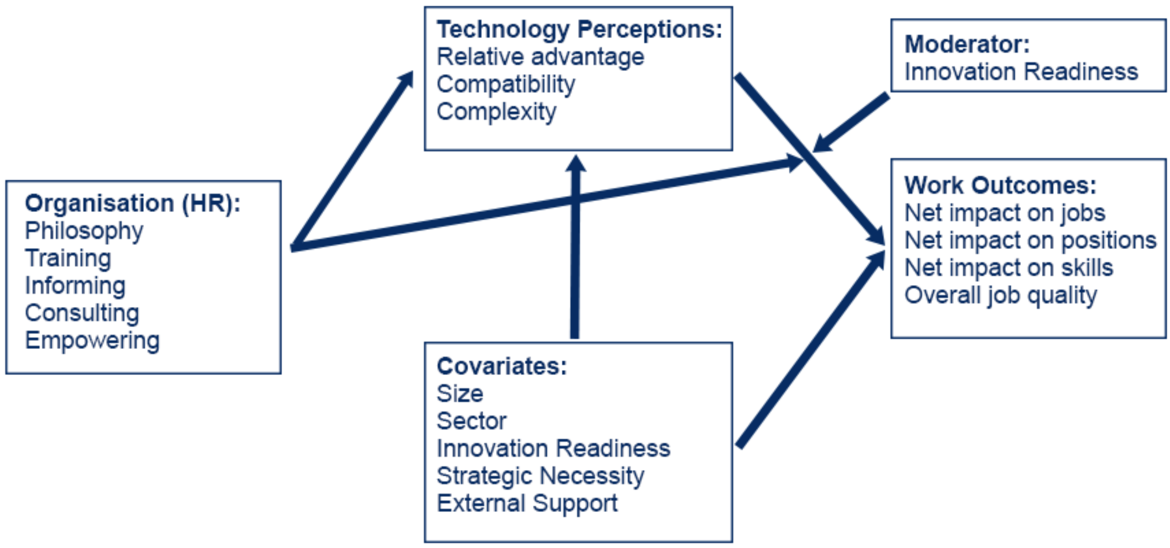
H5: *The extent to which customers or trading partners require adoption of AI technology as a strategic necessity will be positively associated with favourable perceptions of technology.*

H6: *The availability of institutional support for AI technology in the organisation's external environment will be positively associated with favourable perceptions of technology.*

2.3 Impact of Technology Adoption on Jobs, Skills, and Job Quality

The eventual outcome of the adoption of AI depends not only upon the capabilities of the technology itself, but also on resource availability such as knowledge and expertise, managerial philosophy, and employee relations in the organisation (e.g., Barley, 1986; Thomas, 1994). In this study, we focus on three possible impacts of the adoption of AI: on jobs, on skills, and on job quality. This second part of our study addresses the factors influencing these work outcomes within organisations adopting AI for either cognitive or physical task automation. Our framework is summarised in Figure 2.

Figure 2



External to the organisation, differences in institutional arrangements and resources create different contexts for decision-makers choosing whether and how to employ new technologies (Graetz & Michaels, 2017; Kapetaniou & Pissarides, 2023 OECD, 2023). The ability of firms to successfully implement new technologies depends on their access to a well-qualified, motivated, and agile workforce (Autor et al. 2003; Goldin & Katz, 2008; Machin & Van Reenen 1998; Kapetaniou & Pissarides, 2023; WEF, 2018). Continuous investments in human capital are needed to match the growing demand for skills required for the successful adoption of new technologies, and challenges arise when there is a shortage of skills. The availability of an educated workforce creates incentives to adopt technologies that fully leverage the talents of the workforce (Blundell et al., 2022). Access to a skilled workforce and a strong national innovation system create incentives for firms to use new technology to complement rather than displace labour, since this strategy will support long-run competitiveness (Blundell et al., 2022; Carneiro et al. 2023; Kapetaniou & Pissarides, 2023).

Another key factor is the presence of connectivity networks and infrastructure, including the penetration of high-speed internet and broadband services and the coverage of 4G mobile networks, which support a variety of social, economic and developmental goals and enable the adoption of new technologies in a way that contributes to effective enhancement of productivity (Andrews et al., 2018; Kapetaniou & Pissarides, 2023; OECD, 2019c). Although predominantly studied cross-nationally (e.g., Kapetaniou & Pissarides, 2023), there is no reason to expect that the impacts of technology on work outcomes are only influenced by national differences in innovation readiness. At a regional level, work outcomes should be similarly influenced by the availability of these critical resources, creating potential for differential impacts within countries, with consequences for social inclusion and economic inequality. Two regional resource endowments are particularly relevant: regional investments in human capital, and regional connectivity infrastructure. These are conditions that are external to the firm and shape the rate and form of innovation and technology adoption. To the extent that an organisation operates in a region with substantial investments in education, and in which the workforce is better educated and has opportunities for continuous learning, this can support the adoption of technology in ways which complement rather than substitute for tasks and jobs. Thus, in regions exhibiting higher investments in education, there is an incentive for technology implementation strategies that result in net job creation, skill enhancement, and positive impacts on job quality.

In summary, we consider two sets of enabling factors, human capital investments and connectivity infrastructure, which together comprise 'regional innovation readiness'. Regional Innovation Readiness is expected to incentivise investments in technology adoption in ways that are more beneficial to workers. By providing access to a more highly skilled workforce and leveraging better infrastructure, we propose that organisations will have a greater incentive to take a human capital augmenting approach to the implementation of AI technologies rather than a substituting, deskilling approach. Since adoption of new technologies typically places higher demands on skills, all else equal, for those regions where there are higher levels of human capital, there is an incentive for employers to use augmentation strategies that mitigate job displacement, demand higher skill levels, and positively enhance job quality.

H7: *Regional Innovation Readiness positively moderates the association between technology and net job creation, position creation, skills demand, and job quality.*

The principal axis for differentiating management orientation to the workforce is whether human resources are treated as an investment to be nurtured and developed, or as a cost to be minimised (e.g., Lepak et al, 2017). A high-involvement philosophy reflects the philosophy that the workforce is an investment to be developed, which in turn creates value for the organisation. The alternative philosophy treats labour as a replaceable commodity, undifferentiated, and not a strategic source of value. A high-involvement philosophy is more likely to be associated with investments in training programs and skills that facilitate adaptation by the workforce to new technologies and modes of organising.

Investments in training, complemented by the sharing of information about new technologies, consultation on technology adoption, and an orientation towards empowerment and autonomy, are expected to influence whether new technologies have a positive or negative impact on work and workers through three mechanisms (Mirvis et al., 1991). First, a highly skilled workforce will be more likely to understand the need for the new technology, its technical aspects, and its benefits, and feel less threatened by it (OECD, 2023; Lane et al., 2023; Milanez, 2023), this will facilitate approaches to AI adoption in which labour is complemented by technology.

Second, an investment orientation increases the availability of the necessary human and technical capabilities to exploit the new technology creating an incentive for employers to augment rather than substitute labour with technology (Blundell et al., 2022; Kapetaniou & Pissarides, 2023). Equally, for organisations taking a high-involvement approach, there will be a disincentive to eliminate jobs since this would undermine their workforce investments and fail to take advantage of the valuable human capital that has been developed. Since AI tends to automate lower-skilled and routine tasks, it also provides an opportunity to focus on more highly skilled and complex tasks (e.g., Lane et al., 2023; Milanez, 2023) creating a net positive demand for enhanced skills and improving job quality (OECD, 2023).

Third, an investment orientation in which information is shared, and employees have greater voice and autonomy will nurture an organisational context that is more compatible with, and less resistant to the adoption of AI (Doucouliagos, 1995; Morrison, 2011; Trist, 1980). Technology adoption is expected to be more successful, enhance productivity, and promote job satisfaction where employees experience consultation, information sharing, and empowerment which leverage the expertise of employees in the design and development of jobs and work (e.g., Morrison, 2011; Thomas, 1994). Overall, we may expect that a high-involvement approach to HRM creates a context conducive to technology implementation that is complementary rather than substitutive for human resources.

This will be associated with enhancements, rather than reductions to job quality because of upskilling, reduction in routine and mundane tasks, making work on average more interesting, and challenging.

Taken together, this suggests that the presence of high-involvement people management practices, including an investment orientation to employee training, and employee involvement, voice and participation in decision-making, lead to more positive outcomes in terms of job creation, skills development, and net impact on job quality. This leads us to our final hypothesis:

H8: *High Involvement HRM positively moderates the association between technology adoption and net job creation, position creation, skills demand, and job quality.*

3. Data and methods

We test our hypotheses with data from a nationwide employer survey coupled with multiple secondary sources. The survey was conducted by an external agency through a combination of telephone interviews and online surveys. Survey respondents were CEOs, COOs, CTOs, CHROs and equivalent senior executives who could answer affirmatively a screening question "Do you have responsibilities which will allow you to answer questions relating to the adoption of new technologies, and your management practices for your human resources?"

3.1 Sample

The theoretical population for the survey is all UK businesses. A target sample size was set based upon a power analysis. Meta-analyses have estimated that there are at least moderate population effect sizes between management practices, and employer and employee outcome variables (e.g., Combs et al., 2006). Assuming a desired power of .9, a probability level of .05, a conservative assumption of small effect sizes (.02) suggests a minimum sample of n=1,037. We set a target sample of n=1000 firms.

The sampling frame was drawn from the Fame database which contains all detailed annual reports for all UK firms. We limited our frame to organisations with a minimum of 20 employees to ensure there was some formalisation of management practices, as well as sufficient employees to be impacted by technology. Our sampling frame included 74,420 firms, of which 90.1% (67,055 firms) report 20-249 employees, 4.8% (3,572 firms) report 249-499 employees, and 5.1% (3,793 firms) report 500 or more employees. We expect technology adoption to be more common for larger than smaller firms. Since this study is focused on the impacts of AI adoption, we wanted to ensure we obtained a sample in which there was sufficient evidence of adoption. To achieve this, we chose a stratified sampling strategy, in which we oversampled medium and large firms relative to the population, with a target of one third from each of these size categories.

The final achieved sample was n=1012 of which 435 firms (42.9%) report 20-249 employees, 208 firms (20.6%) report 250-249 employees and 369 firms (36.5%) report 500+ employees. All industry sectors are represented, with the largest share of organisations in Financial Services (19.3%), Information and Communication Services (15.4%), Manufacturing (12%), and Professional, Scientific and Technical Activities (10.4%). The average experience for respondents (senior executives) in their organisation was 9.3 years.

3.2 Measures

Dependent Variables

We measure two different sets of outcomes in this study. The first is technology adoption; the second set measure the impacts of technology adoption on jobs, positions, skills, and quality of work. Technology adoption is measured using two single-item measures from Hunt et al. (2020) addressing the automation of physical and cognitive tasks: "In the last three years, we have introduced AI, robotic or automated equipment to undertake a physical task" and "In the last three years, we have introduced AI, robotic or automated software to undertake a cognitive/non-physical task."

Our second set of dependent variables relate to the Impact on Jobs, Impact on Positions (i.e., where more than one person holds a job type, these are positions), Impact on Skills, and Impact on Job Quality. Only those responding affirmatively to one or both technology adoption questions were asked these questions. First, we ask whether new jobs/positions have been created or, equally, are new skills needed in response to technology adoption (e.g., "Has the introduction of new technology created any new jobs in your organisation?" (Yes/no)). Then we ask whether new jobs/positions have been eliminated or established skills are no longer required (e.g., "The introduction of new technology has eliminated or reduced the need for some skills in this organisation" (Yes/no)). We then ask what the net impact is overall on jobs/positions/skills (e.g., "Overall, has the introduction of AI, robotic or automated equipment led to more or fewer positions in your organisation?"). The 'net impact' questions used a five-point response format: 'a lot more' (5); 'a few more' (4); 'no change' (3); 'a few less' (2); 'a lot less' (1).

For the impact on Job Quality, interviewers asked respondents "Overall, what do you think the overall impact of new process technology will be upon the quality of the job for the typical employee affected by it?" Interviewers also read the following definition "By job quality, we would consider factors like pay, hours, doing interesting and meaningful work, having opportunities for personal development, and being able to have a say about issues in the workplace." Interviewers then asked "As a result of the new process technology, will overall job quality be expected to increase, stay the same, or be reduced over time? Will the technology impact these aspects of work on average in a positive or negative way?" Interviewers then followed up with a probe, if the answer was better/positive, "very much (5) or a little (4)?" if the answer was worse/negative, interviewers probed "a little (2) or a lot (1)?"

Independent Variables

We base our measures of technology perceptions on the measures developed by Moore and Benbasat (1991) which focus on three perceived qualities of the technologies. The Relative Advantage (perceived usefulness) scale has five items (example items include: "Using the AI/Robotic Automation… enable(s) us to accomplish tasks more quickly"; "… enable(s) us to improve quality"; "…make(s) it easier to perform important production/ service or administrative tasks"). There is evidence of good internal consistency reliability and construct validity for this measure (Moore & Benbasat, 1991). Since we are interested in technology perceptions for both adopters and non-adopters, these questions were modified with the wording of 'enables us' for adopters and 'would enable us' in the case of respondents who had not (or not yet) adopted the technology. A five-point agree-disagree response format is used for this and all subsequent measures unless otherwise noted. Perceived Compatibility of the technology is measured with three items (Moore & Benbasat, 1991): "Using the AI/Robotic Automation… (would) fit(s) well within our operations"; "… fit(s) well with our work style"; "…is/would be compatible with all aspects of our activities." Perceived Complexity of the technology is measured with three items (Moore & Benbasat, 1991): "AI/Robotic Automation… is/would be easy to apply and implement for our use case"; "…is/would be easy to learn how to operate"; "…overall is/would be easy to use."

Regional Innovation Readiness is measured using data from the recently created Disruption Index (IFOW, forthcoming). The Regional Innovation Readiness aggregated score reflects the equally weighted human capital and infrastructure dimensions expected to provide important resources that can support the adoption and implementation of innovative new technologies in the workplace (see Table I). Data sources for this index are the Office for National Statistics, Eurostat, and the OECD. This data is mapped from NUTS2 regions onto UK counties in which the primary business is based.

Table I: The Dimensions and Indicators Contributing to the Regional Innovation Readiness Index

Dimension	Sub-dimension	Indicators
Human Capital	Basic skills	Overall levels % with NVQ4+
		GCSE attainment
		Pupil-teacher ratio funded schools
	Investment in education	Government investment in education (total)
		Government investment in education per pupil
	Post-secondary education	ICT apprenticeships
		Enrolment in tertiary education
		Number of postgraduates
	Adult education	Lifelong learning
		On the job training
	Workforce composition	LF participation rates
		Working age population
Infrastructure	ICT	4G mobile coverage
		Internet download speed
		Ultrafast internet availability
		Number of internet users

Human Resource Management (HRM) philosophy and practices are measured using multiple subscales. The decision to use these subscales rather than a general 'high-performance work practices' scale was based on two reasons. First, while general scales cover the breadth of an HR system, these typically provide only a single item for each domain. Thus, areas of central interest to this study such as employee consultation and workforce training and development would each be measured with a single item. In some cases, there are no specific items for the areas we are interested in (e.g., informing employees about new technologies; consulting employees around technology use). We therefore preferred to use multi-item scales for each of the practices of interest trading breadth of the entire HR system, for depth and precision in measurement of these focal constructs.

HR Philosophy (Lepak et al., 2007) reflects the general orientation towards treating employees and the workforce as a long-term investment rather than a cost. Since HRM systems become more formalised as organisations grow larger and more established, measures of HRM systems may privilege large organisations over SMEs. In contrast, HR philosophy has the advantage of being agnostic of firm size and age. This was measured using four items from Lepak et al. (2007). A sample item is "We invest heavily in our employees because we know that they determine the success of our business." Informing Employees about new technologies is assessed using three items from the UK Workplace Employment Relations Survey (WERS: UK Department of Business Innovation and Skills, 2011): "We do a good job of keeping employees informed of ways in which new work technologies will change the way the organisation is run"; "We do a good job in informing our workforce of ways that new technologies are expected to lead to future changes in staffing"; "We keep the workforce informed over expected changes in their work tasks as a result of the adoption of new technologies."

Consulting Employees about new technologies is assessed using three items from the WERS: "When we are considering adopting new technologies, we seek the views of employees or employee representatives", "When we are considering adopting new technologies, we respond to the suggestions from employees or employee representatives", "When we are considering adopting new technologies, we allow employees or employee representatives to influence the final decision."

Employer Attitude Towards Training is measured using five items from Bae and Lawler (2000). Sample items include "Relative to our peers and competitors, we spend an above average amount of money on training"; "We provide above average opportunities for training"; "We make a wide range of different kinds of training available to employees." Employer Attitudes Towards Empowerment are measured using five items from Bae and Lawler (2000). Sample items include "We seek engagement of employees at all levels in problem-solving and decisions"; "Employees here have lots of opportunities to use their personal initiative"; "Employees are given significant discretion in how they perform their work"; "We have a very cooperative and trustful climate."

We measure organisational size based upon the self-reported number of employees. This was converted to a log scale for the analysis as it is skewed towards the lower end of the distribution.

Strategic Necessity is measured using three items (Premkumar, 2003): "We will lose customers to our competitors if we do not adopt these new technologies"; "It is a strategic necessity to use these technologies to compete in the marketplace"; "Our customers require the use of these technologies for doing business with them."

Institutional Support for technology adoption is measured using two items (Premkumar, 2003): "We are able to access support such as the knowledge and information needed for the adoption of these new technologies, for example, from Government agencies, Local Enterprise Partnerships or Enterprise Zones, Industry Associations, and/or local Universities and colleges etc."; and "We are able to access any needed financial support for investments in these new technologies from investors, banks and other sources."

In addition, we include industry sector as a control variable on the expectation that different sectors will have different propensities to technology adoption and implementation driven by concentration, knowledge intensity and capital intensity. To control for this, we include categorised industry sector following the 19 sections of the UK SIC hierarchy. This data was obtained from the Fame database.

4. Results

4.1 Preliminary Analysis

All multi-item scales were subjected to exploratory factor analysis and internal consistency analyses to assess whether the individual items converged in the expected ways. Estimates of internal consistency reliability are summarised in Table II below. All but one scale achieves a satisfactory or better level of internal consistency, reflecting that the items in the scales are closes related. The exception to this is the measure of External Support from our context variables, which falls below the desired threshold of .70. This may be attributed to the small number of items (two) in that subscale (Cortina, 1993).

Table II: Internal Consistency Reliability

Scale	Cronbach's Coefficient Alpha
Relative Advantage (5 items)	0.834
Compatibility (3 items)	0.801
Complexity (3 items)	0.819
Strategic Imperative (3 items)	0.745
External Support (2 items)	0.632
HR Philosophy (3 items)	0.746
HR Inform (3 items)	0.698
HR Consult (3 items)	0.714
HR Train (6 items)	0.825
HR Empower (7 items)	0.804
Technology Perceptions (Combined 11 items)	**0.911**
High Involvement HRM (Combined 22 items)	**0.928**

A confirmatory factor analysis of the HRM items suggests a second-order factor structure in which the first-order latent sub-dimensions load onto a second-order latent factor which we call 'High-Involvement HRM'. Item two in the HR Philosophy scale loaded poorly and was dropped. A second-order factor solution achieves the best fit (Chi-square 643.427; 204df $p<.001$; NFI = .927; TLI=.937; CFI=.949; RMSEA .046). For our main analysis, in which we will use PROCESS (Hayes, 2022), we created an aggregate variable taking the mean across the subscales. The pooled items achieve a high internal consistency reliability (Cronbach's alpha=.928) supporting this aggregation.

A similar result is obtained for the technology items. That is, the items for Relative Advantage, Complexity, and Compatibility all load onto their respective factors in an exploratory analysis. However, a confirmatory factor analysis offers support for a second-order factor in which the three subdimensions load onto a second-order aggregate latent factor which we label ‘Technology Perceptions’ (Chi-square 237.788; 41df p<.001; NFI = .957; TLI=.942; CFI=.964; RMSEA .069). We created an aggregate variable for Perceptions of Technology by taking the mean across the three subscales. The estimated Cronbach’s coefficient alpha when we pool all 11 items is .911.

Table III shows the means, standard deviations, and correlations of the variables in our analysis. In our sample of n=1012 respondents, 79.2% reported affirmatively that their organisation had adopted AI, robotic, or automated equipment to undertake a physical task; while 78.8% reported that their organisation had adopted AI, robotic, or automated equipment to undertake a cognitive or non-physical task. We note that neither Technology Adoption measures are correlated with impacts on Job Quality, or Regional Innovation Readiness. Furthermore, Regional Innovation Readiness is not correlated with Job Quality or External Support. This pattern of correlations is consistent with the hypothesised indirect relationships.

Table III: Means, Standard Deviations, Correlations

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11
1. Adopt Physical	0.79	.406	--										
2. Adopt Cognitive	0.79	.409	.616**	--									
3. Net Impact on Jobs	3.47	.932	.116**	.085**	--								
4. Net Impact on Positions	3.53	.919	.135**	.086*	.671**	--							
5. Net Impact on Skills	3.73	.819	.061	.094**	.496**	.455**	--						
6. Impact on Job Quality	3.85	.825	.036	.036	.328**	.318**	.416**	--					
7. Technology Perceptions	3.94	.704	.448**	.380**	.246**	.242**	.185**	.149**	--				
8. Strategic Imperative	11.41	2.467	.393**	.340**	.204**	.244**	.180**	.149**	.706**	--			
9. External Support	7.63	1.594	.289**	.235**	.218**	.196**	.177**	.149**	.596**	.517**	--		
10. Reg. Inn. Readiness	0.63	.107	.038	.063	.096**	.087*	.128**	.061	.068*	.070*	.033	--	
11. HRM (overall)	3.97	.552	.209**	.162**	.264**	.219**	.197	.192**	.576**	.512**	.566**	.033	
12. HRM x Technology	15.89	4.362	.385**	.323**	.300**	.272**	.224**	.199**	.912**	.694**	.658**	.054	.849**

Note: Significant correlations highlighted in bold. ** p<.01 * p<.05

Of the 864 organisations that have adopted at least one of the new technologies, 684 (78%) report that the introduction of new technology has created new jobs; while 483 (55.3%) report that the introduction of new technology has eliminated or replaced jobs. Since any particular job role may have many or few instances, it is instructive to assess the impact on positions as well as jobs. Of the 864 respondents adopting technology, 674 (66.6%) report that the introduction of the new technology has created new positions, while 478 (47.2%) report that it has eliminated positions. Of these 864, 717 (83%) report that the introduction of new technology has increased the need for new skills in the organisation, while 466 (53.9%) report that the technology has reduced the need for some skills. These numbers reflect the fact that for some jobs, skills requirements are increasing, while at the same time for other jobs within the same organisation, the demand for certain skills is reduced. Turning to job quality, 69.3% report that they believe that job quality is improved a little (48%) or a lot (21.3%), while 4.9% believe that job quality is reduced by a little (4.4%) or a lot (0.5%). 219 respondents (21.3%) expected no change. Thus, the overall picture leans towards net positive effects on job quality. Our main analysis will explore this in greater detail to understand the contingencies for positive versus negative outcomes.

4.2 Analysis for Technology Adoption

Our conceptual framework links three sets of factors to technology adoption: technology factors, organisation factors, and environment factors. We use Hayes' PROCESS (Model 4) to evaluate the direct and indirect effects of these factors on Technology Adoption through the mediating variable of Technology Perceptions. We examine these relationships in the case of two purposes of adoption: for physical tasks, and for cognitive tasks. Although the mediating variable is continuous, the dependent variable is binary. However, the PROCESS macro can accommodate this difference (Hayes, 2022).

Physical Tasks

In the first model, we estimate the relationships between independent variables and the mediating variable, Technology Perceptions. Overall, model 1 is significant (R-square .601; p<.001). For the overall model 2 (binomial logistic), estimating the association with Technology Adoption for physical tasks, the Hosmer and Lemeshow test is non-significant (Chi-Square 7.734, 8df, p=.460), supporting overall model fit. The pseudo-R-Square is .254, and corrected pseudo-R-square is .396 indicating a meaningful amount of variance in technology adoption is explained by this model. The overall percentage of correct classifications is 83.8% which further supports model fit. The model coefficients and their significance are summarised in Table IV overleaf.

Industry sectors are included as dummy variables where the reference group is the 'Other Services' sector. In model 1, where the mediator Technology Perceptions is treated as the dependent variable, we find that Manufacturing, Construction, Transportation and Storage, Information and Communication, Financial and Insurance, Real Estate, Professional, Scientific and Technical Activities, are all positive and significant at p<.05 or less, and Health and Social Work is marginally significant (p<.10). These sectors are more likely to have positive Technology Perceptions in contrast to Other Services. In model 2, where Technology Adoption for Physical Tasks is the dependent variable, we note that Accommodation and Food Services are marginally significant (Exp(B) .227; p<.1), Administrative and Support Service Activities (Exp(B) .165; p<.1), Public Administration & Defence is significant (Exp(B) .09; p<.05), and Art, Entertainment and Recreation (Exp(B) .075; p<.01). These estimates indicate these sectors are significantly less likely to adopt technology for physical tasks than the contrast sector 'Other Services'. The difference in the number of significant coefficients between models 1 and 2 is suggestive that sectoral differences influence Technology Perceptions and once this is included in model 2, this accounts for the sector-level differences.

Size, measured as the natural log of the number of employees, is non-significant in model 1, suggesting it does not influence technology perceptions, **contrary to hypothesis 4a**. However, size is significant (Exp(B) 1.189; p<.05) in model 2, **supporting hypothesis 4b**, that larger organisations are more likely to adopt AI and robotic technology for physical tasks than smaller organisations.

Regional Innovation Readiness is not significant across either model, indicating no main effects for this variable. Supporting hypothesis 5, Strategic Necessity is positively and significantly associated with Technology Perceptions (p<.001). **Supporting hypothesis 6**, External Support is positively associated with Technology Perceptions (p<.001).

Table IV: HRM Mediated by Perceptions of Technology on Tech Adoption for Physical Tasks

<table>
<tr><th></th><th colspan="2">Model 1: Mediator Technology Perceptions</th><th colspan="3">Model 2: Outcome Adoption for Physical Tasks</th></tr>
<tr><td>Independent Variables in the Equation</td><td colspan="2">Coefficient (B)</td><td colspan="3">Coefficient (B)</td></tr>
<tr><td>Agriculture, Forestry & Fishing</td><td colspan="2">.422</td><td colspan="3">-2.123</td></tr>
<tr><td>Mining & Quarrying</td><td colspan="2">.214</td><td colspan="3">.859</td></tr>
<tr><td>Manufacturing</td><td colspan="2">.287**</td><td colspan="3">-.021</td></tr>
<tr><td>Electricity, Gas, Steam & Air Conditioning Supply</td><td colspan="2">.115</td><td colspan="3">.589</td></tr>
<tr><td>Water Supply; Sewerage, Waste Mgt & Rem.</td><td colspan="2">.086</td><td colspan="3">-.987</td></tr>
<tr><td>Construction</td><td colspan="2">.269**</td><td colspan="3">-.340</td></tr>
<tr><td>Wholesale & Retail Trade; Repair of Motor Veh.</td><td colspan="2">.204</td><td colspan="3">13.258</td></tr>
<tr><td>Transportation & Storage</td><td colspan="2">.376**</td><td colspan="3">-.450</td></tr>
<tr><td>Accommodation & Food Service Activities</td><td colspan="2">.215</td><td colspan="3">-1.482†</td></tr>
<tr><td>Information & Communication</td><td colspan="2">.256*</td><td colspan="3">-.693</td></tr>
<tr><td>Financial & Insurance Activities</td><td colspan="2">.221*</td><td colspan="3">-.256</td></tr>
<tr><td>Real Estate Services</td><td colspan="2">.279*</td><td colspan="3">-.990</td></tr>
<tr><td>Professional, Scientific & Technical Activities</td><td colspan="2">.318*</td><td colspan="3">-.947</td></tr>
<tr><td>Administrative, & Support Service Activities</td><td colspan="2">.070</td><td colspan="3">-1.804†</td></tr>
<tr><td>Public Admin & Defence; Compulsory Social Sec.</td><td colspan="2">.252</td><td colspan="3">-2.368*</td></tr>
<tr><td>Education</td><td colspan="2">.193</td><td colspan="3">-1.300</td></tr>
<tr><td>Human Health & Social Work Activities</td><td colspan="2">.229†</td><td colspan="3">-.832</td></tr>
<tr><td>Arts, Entertainment & Recreation</td><td colspan="2">.181</td><td colspan="3">-2.593**</td></tr>
<tr><td>Employees (Ln)</td><td colspan="2">.0155</td><td colspan="3">.173*</td></tr>
<tr><td>Regional Innovation Readiness</td><td colspan="2">.208</td><td colspan="3">-.693</td></tr>
<tr><td>Strategic Necessity</td><td colspan="2">.135***</td><td colspan="3">.180**</td></tr>
<tr><td>External Support</td><td colspan="2">.107***</td><td colspan="3">.042</td></tr>
<tr><td>HRM</td><td colspan="2">.254***</td><td colspan="3">-363</td></tr>
<tr><td>Technology</td><td colspan="2"></td><td colspan="3">1.540***</td></tr>
<tr><td></td><td colspan="2">R-sq .601</td><td colspan="3">Nagelkerke Pseudo-R-sq .386</td></tr>
<tr><td></td><td colspan="2">F 55.469***</td><td colspan="3">Chi-Sq 24 df p<.001</td></tr>
<tr><td>Direct Effects of X (HRM) on Y (Adoption): -.363</td><td>se .2395</td><td>Z -1.513</td><td>p .130</td><td>LLCI -.832</td><td>ULCI .107</td></tr>
<tr><td>Indirect Effects of X (HRM) on Y (Adoption): .391</td><td colspan="2">Boot SE .092</td><td>Boot LLCI .255</td><td colspan="2">Boot ULCI .609</td></tr>
</table>

Supporting hypothesis 1, Technology Perceptions, when included in model 2, have a significant and strong positive association with Technology Adoption (Exp(B) 4.665; $p<.001$). This estimate suggests that a unit change in Technology Perceptions increases the probability of Technology Adoption by more than 4 times, all else equal.

HRM is significantly associated with Technology Perceptions ($p<.001$) supporting hypothesis 2. Furthermore, there is not a main effect of HRM on Technology Adoption. Using Hayes' PROCESS (Model 4), the bootstrapped estimates of lower and upper confidence intervals do not include zero and the estimated indirect effect is .391. **This supports hypothesis 3**, that Technology Perceptions fully mediate the association between HRM and Technology Adoption.

Cognitive Tasks

In the first model, we again estimate the relationships between independent variables and the mediating variable, Technology Perceptions. The results are summarised in Table V. Model 1 is the same as for the prior analysis. For model 2 overall, the results suggest a good model fit (Hosmer & Lemeshow test Chi-square 7.408, 8df, $p=.493$). The Pseudo R-square (.177) and corrected Pseudo R-Square (.273) indicate a meaningful degree of variance explained in the dependent variable by the predictors. The overall classification rate of 82.5% correct is at an acceptable level.

Notably, in model 2 there are no significant estimates for any of the industry sectors, suggesting that these differences are expressed via their association with Technology Perceptions rather than directly on Technology Adoption. Organisation size is not significantly associated with either mediator or dependent variable. **This is contrary to hypotheses 4a and 4b** and implies that size is not an important factor differentiating adopters from non-adopters when it comes to AI technologies.

Strategic Necessity and External Support are significant predictors of the Technology Perceptions, consistent with hypotheses 5 and 6. Perceptions of Technology are positively and significantly associated with Technology Adoption (Exp(B) 2.889; $p<.001$) which estimates that for a unit increase in Technology Perceptions, there would be close to three times the probability of adopting technologies to perform cognitive tasks. **This supports hypothesis 1**.

The overall model shows that there is a significant indirect association between HRM and Technology Adoption for cognitive tasks, with the bootstrapped 95% confidence interval not including zero, and with an estimated indirect effect size of .269. Furthermore, the results indicate that the direct association between HRM and Technology Adoption is not significant, suggesting that Perceptions of Technology fully mediate the association of HRM with Technology Adoption for cognitive tasks. **This supports hypothesis 3.**

Table V: HRM Mediated by Perceptions of Technology on Tech Adoption for Cognitive Tasks

	Model 1: Mediator Technology Perceptions		**Model 2: Outcome Adoption for Cognitive Tasks**		
Independent Variables in the Equation	**Coefficient (B)**		**Coefficient (B)**		
Agriculture, Forestry & Fishing	.422		--.089		
Mining & Quarrying	.214		1.232		
Manufacturing	**.287****		-.275		
Electricity, Gas, Steam & Air Conditioning Supply	.115		1.092		
Water Supply; Sewerage, Waste Mgt & Rem.	.086		-.361		
Construction	**.270***		.061		
Wholesale & Retail Trade; Repair of Motor Veh.	.204		13.859		
Transportation & Storage	**.376****		-.313		
Accommodation & Food Service Activities	.215		**-.663**		
Information & Communication	**.256***		-.128		
Financial & Insurance Activities	**.221***		.258		
Real Estate Services	**.279***		.217		
Professional, Scientific & Technical Activities	**.318****		.239		
Administrative, & Support Service Activities	.070		**.912**		
Public Admin & Defence; Compulsory Social Sec.	.252		**-.393**		
Education	.193		-.428		
Human Health & Social Work Activities	.229†		-.037		
Arts, Entertainment & Recreation	.181		**-.746**		
Employees (Ln)	.016		**.093**		
Regional Innovation Readiness	.208		.797		
Strategic Necessity	**.135*****		**.141**		
External Support	**.107*****		.039		
HRM	**.254*****		-.284		
Technology			**1.061*****		
	R-sq .60		Nagelkerke Pseudo-R-sq .253		
	F 55.469***		Chi-Sq 24 df p<.001		
Direct Effects of X (HRM) on Y (Adoption): -.284	se .218	Z -1.303	p .193	LLCI -.711	ULCI .143
Indirect Effects of X (HRM) on Y (Adoption): .269	Boot SE .074		Boot LLCI .154	Boot ULCI .439	

4.3 Analysis of Technology and Work Outcomes

In this second part of the analysis, we include only those firms which report having already adopted AI, to understand how our moderating variables interact with Technology Perceptions and whether these contingencies explain differences in work outcomes. We use Hayes' PROCESS (Model 14) to examine the hypothesised mediating model with two moderators. The results are summarised in Table VI. This involves first a regression (model 1) of the antecedents to the mediator (Technology Perceptions). Model 1 is significant overall (R-squared .535, $p<.001$) and we observe significant positive associations for Manufacturing (.232 $p<.001$), Transportation and Storage (.419, $p<.001$), Information and Communication (.225, $p<.05$), Real Estate Services (.295, $p<.05$), and Professional, Scientific and Technical Activities (.283, $p<.05$), with Construction (.223, $p<.1$) also positive and marginally significant. These estimates indicate that in these sectors, Perceptions of Technology are more positive in contrast to the Other Services sector. We also observe that Strategic Necessity (.081, $p<.001$), External Support (.097, $p<.001$) and HRM (0.361, $p<.001$) are significantly associated with Perceptions of Technology, which is hypothesised to mediate the impact on our outcomes of interest.

We then run a second model for each of the outcomes of interest which includes the mediator and the moderators: model 2 for the Net Impact on Jobs, model 3 for the Net Impact on Positions, model 4 for the Net Impact on Skills, and model 5 for overall impact on Job Quality. In these subsequent models, we include the mediator variable, Perceptions of Technology, our hypothesised main moderator, Regional Innovation Readiness, and the interaction effect, which is the product of Perceptions of Technology and Regional Innovation Readiness. The PROCESS macro for model 14 also calculates the second mediating effect of interest, which is the interaction between Perceptions of Technology and HRM.

Model 2 examines the outcome of Net Impact on Jobs. This model is significant overall (R-squared 153, $p<.001$), and the Index of Moderated Mediation is estimated as .420 with the bootstrapping process estimating that the 95% confidence interval does not include zero (lower CI .032; upper CI .831). This is evidence that Perceptions of Technology mediate the relationship between High-involvement HRM and the Net Impact on Jobs. That is, through the positive influence on Perceptions of Technology, HRM is associated with a positive Net Impact on Jobs. Supporting hypothesis 7, model 2 shows that the interaction between Technology Perceptions and Regional Innovation Readiness is positive and significantly associated with Net Impact on Jobs (1.165, $p<.05$).

To illustrate the moderation effect, we conducted a simple slopes analysis, which is shown in Figure 3a. In this analysis, we compare the association between the mediator, Perceptions of Technology, and the outcome, Net Impact on Jobs, for three levels of the moderator, Regional Innovation Readiness, at the sample mean value, and one standard deviation above and below the mean. It is clear that there is a positive impact on the association, and it is only at a high level of Regional Innovation Readiness, that the bootstrap coefficient estimates do not include zero within the 95% confidence interval. This indicates that Perceptions of Technology are positively associated with Net Job Creation, but only when Regional Innovation Readiness is high.

Table VI: Impacts of Technology, Organisational, and Environmental Factors on Jobs, Positions, Skills and Job Quality

	1. Technology		2. Net Jobs		3. Net Positions		4. Net Skills		5. Job Quality	
Independent Variables in the Equation	B	Se	B	Se	B	Se	B	Se	B	Se
Agriculture, Forestry & Fishing	.318	.311	.525	.666	1.531*	.663	.490	.601	.115	.597
Mining & Quarrying	.235	.188	-.491	.404	.332	.402	-.509	.364	-.135	.362
Manufacturing	.232***	.111	.036	.241	.023	.240	-.125	.217	-.336	.216
Electricity, Gas, Steam & Air Conditioning Supp.	.056	.146	-.247	.314	.001	.312	-.298	.283	-.996***	.281
Water Supply; Sewerage, Waste Mgt & Rem.	.373	.260	1.428*	.557	1.130†	.555	.385	.503	-.011	.500
Construction	.223†	.118	.096	.255	.037	.254	-.204	.230	-.409†	.228
Wholesale & Retail Trade; Repair of Motor Veh.	.082	.173	.292	.370	.252	.368	.372	.334	-.099	.332
Transportation & Storage	.419***	.125	-.033	.270	.014	.269	-.098	.244	-.337	.242
Accommodation & Food Service Activities	.119	.142	.175	.305	.332	.304	.107	.275	-.348	.273
Information & Communication	.225*	.110	.293	.235	.309	.234	-.001	.212	-.384†	.211
Financial & Insurance Activities	.162	.108	.139	.232	.242	.231	-.022	.209	-.307	.208
Real Estate Services	.295*	.136	-.503†	.292	-.128	.291	-.405	.263	-.208	.262
Professional, Scientific & Technical Activities	.283*	.113	.165	.243	.164	.242	.026	.219	-.397†	.218
Administrative, & Support Service Activities	.016	.167	.065	.358	.035	.356	-.096	.323	-.668*	.321
Public Admin & Defence; Compulsory Soc. Sec.	.292	.198	-.570	.425	-.549	.423	.299	.383	-.592	.381
Education	.177	.137	-.245	.296	-.269	.295	-.202	.267	-.668*	.266
Human Health & Social Work Activities	.099	.131	-.056	.282	.131	.281	.112	.254	-.266	.253
Arts, Entertainment & Recreation	.161	.172	.450	.369	.219	.367	.043	.333	-.068	.331
Strategic Imperative	.081***	.009	.009	.020	.054**	.020	.020	.018	.027	.018
External Support	.097***	.013	.039	.028	.016	.028	.037	.026	.033	.026
HRM*	.361***	.039	.267**	.088	.134	.087	.127	.079	.225**	.078
Technology			-.604†	.080	.757*	.344	-.530†	.311	-.812**	.309
Regional Innovation Readiness			-4.145*	2.120	-5.235*	2.111	-3.269†	1.912	-4.971**	1.901
Technology x Regional Innovation Readiness			1.165*	.519	1.438**	.517	.983*	.468	1.269**	.465
R-sq (F)	.535 (39.435***)		.153 (5.386***)		.144(5.007***)		.097(3.211***)		.100 (3.319***)	
Index of Moderated Mediation			.420		.519		.355		.458	
Boot LLCI			.032		.145		.017		.100	
Boot ULCI			.831		.937		.731		.797	

Note: *PROCESS model 14 estimates of the second interaction term (TechnologyxHRM) and provides an F test as follows: Jobs, F 15.973, p<.001; Positions, F 12.841, p<.001; Skills, F 5.418, p<.05; Job Quality, F 4.282, p<.05.

We find a significant main effect (.267, $p<.01$) for HRM on Net Impact on Jobs, and supporting hypothesis 8, the interaction between Perceptions of Technology and HRM on the same dependent variable to be statistically significant (F 15.973, p.<001). Thus, HRM not only serves as an antecedent to Perceptions of Technology but also moderates the relationship between these perceptions and net job creation.

In model 3 we repeat this analysis for the Net Impact on Positions. As can be seen from Table VI, model 3, the results closely mirror those for model 2, without main effects for either External Support or for HRM. The model is again significant overall (R-squared .144, $p<.001$). There are significant interaction effects for both Perceptions of Technology by Regional Innovation Readiness (1.438, $p<.01$), supporting hypothesis 7 and for Perceptions of Technology by HRM (F 12.841, $p<.01$) supporting hypothesis 8. The overall Index of Moderated Mediation is .519 and the bootstrapped confidence limits do not include zero (BootLLCI .145; BootULCI .937). Simple slopes analysis is shown in Figure 3b which illustrates that the association between Perceptions of Technology and the Net Impact on Positions is significantly more positive where Regional Innovation Readiness is one standard deviation above the mean.

Figure 3a

Net Impact of Technology Perception on Jobs, moderated by Regional Innovation Readiness

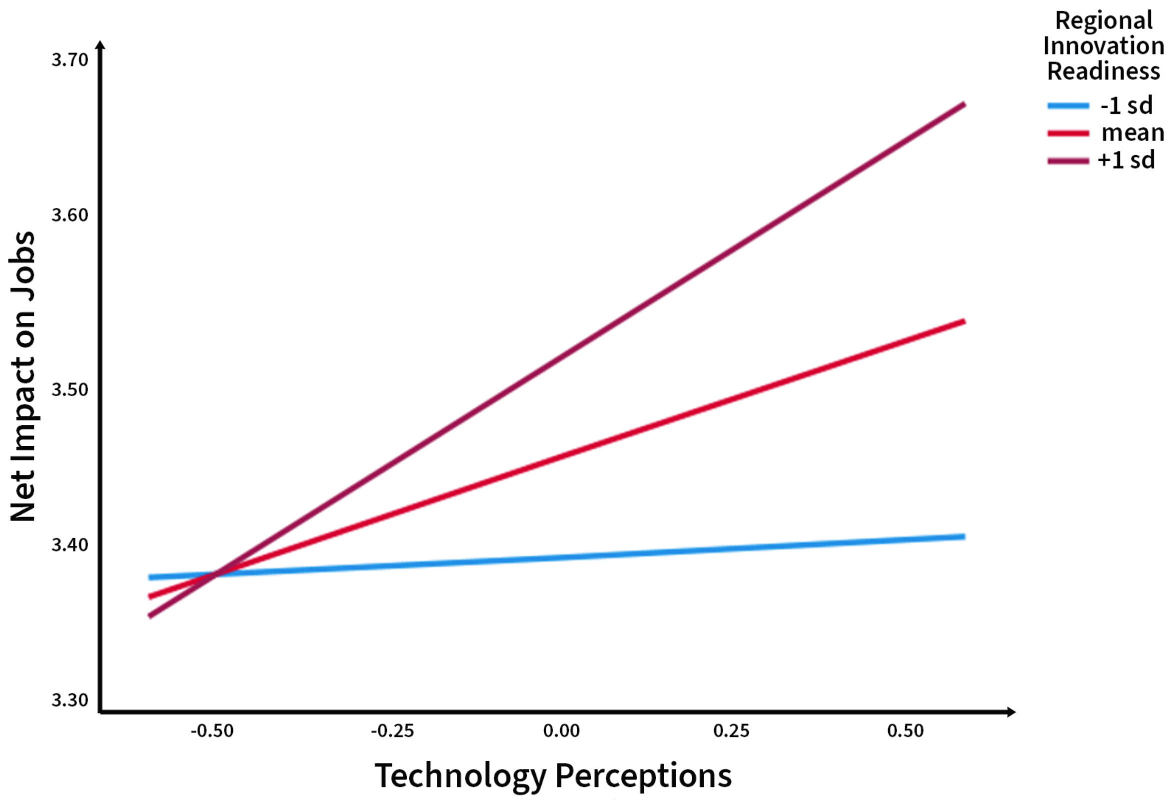


Figure 3b

Net Impact of Technology Perception on Positions, moderated by Regional Innovation Readiness

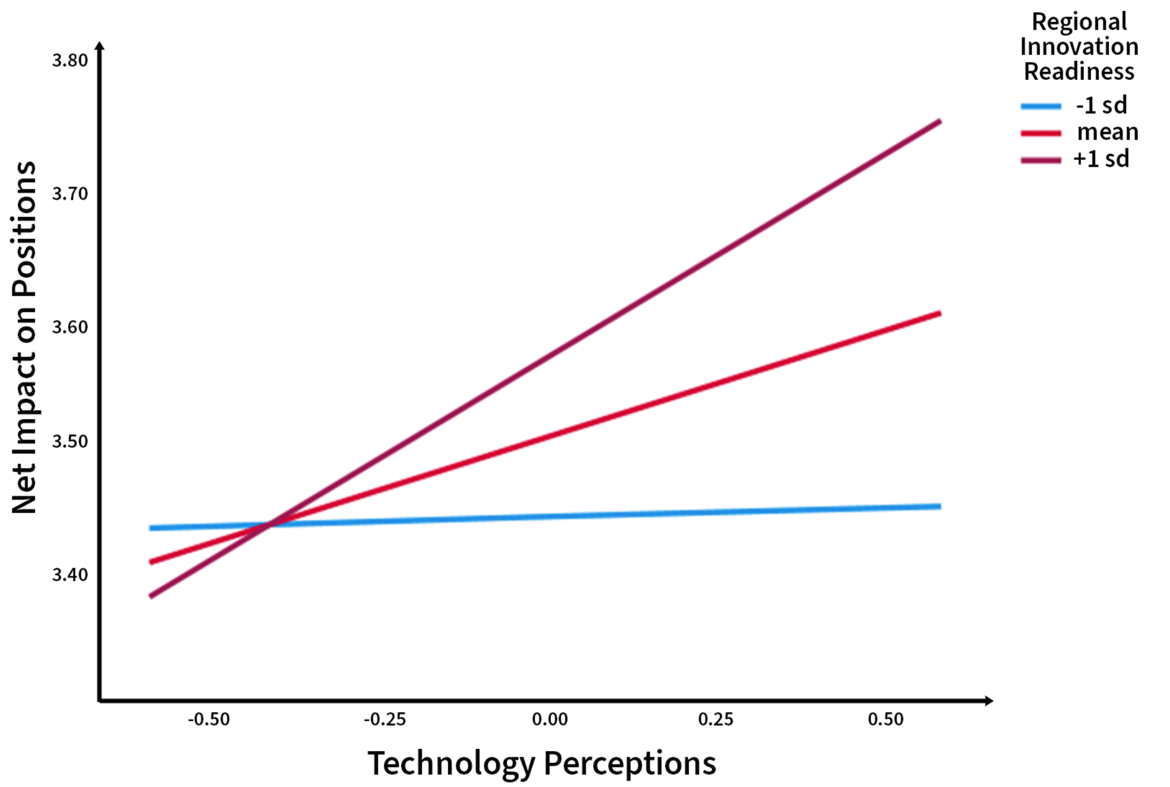


Figure 3c

Net Impact of Technology Perception on Skills, moderated by Regional Innovation Readiness

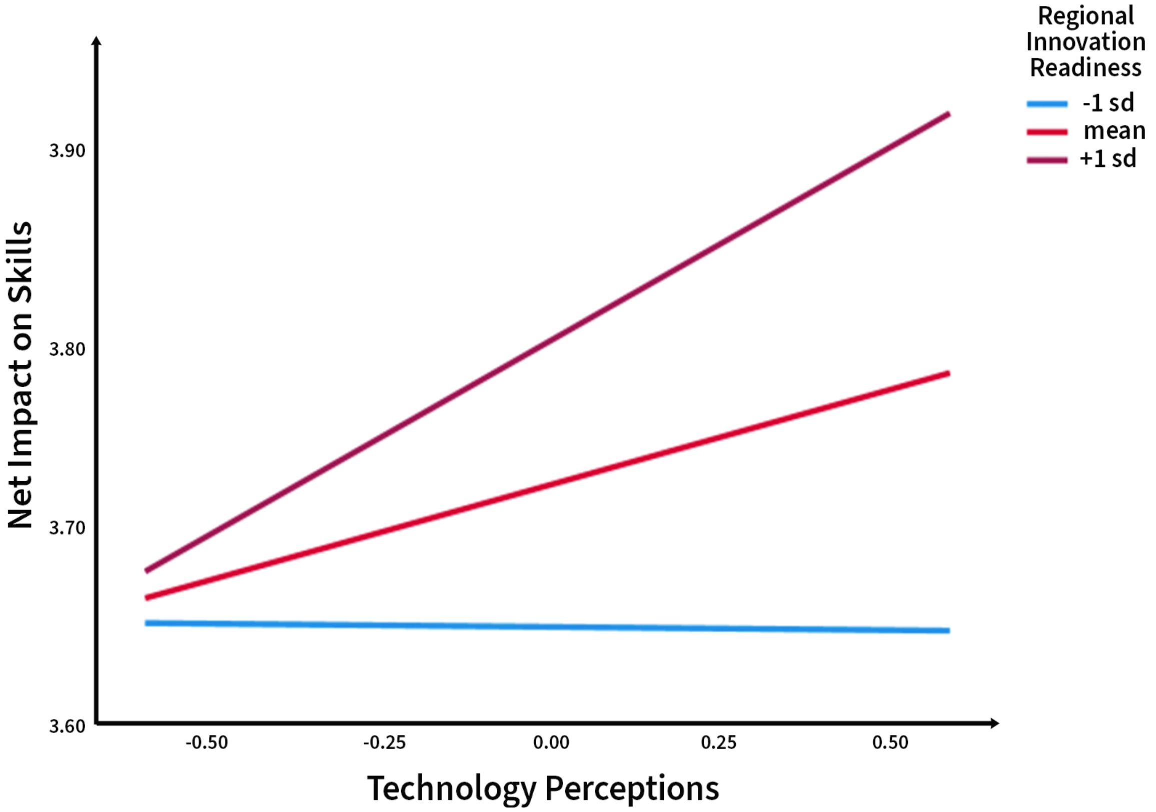
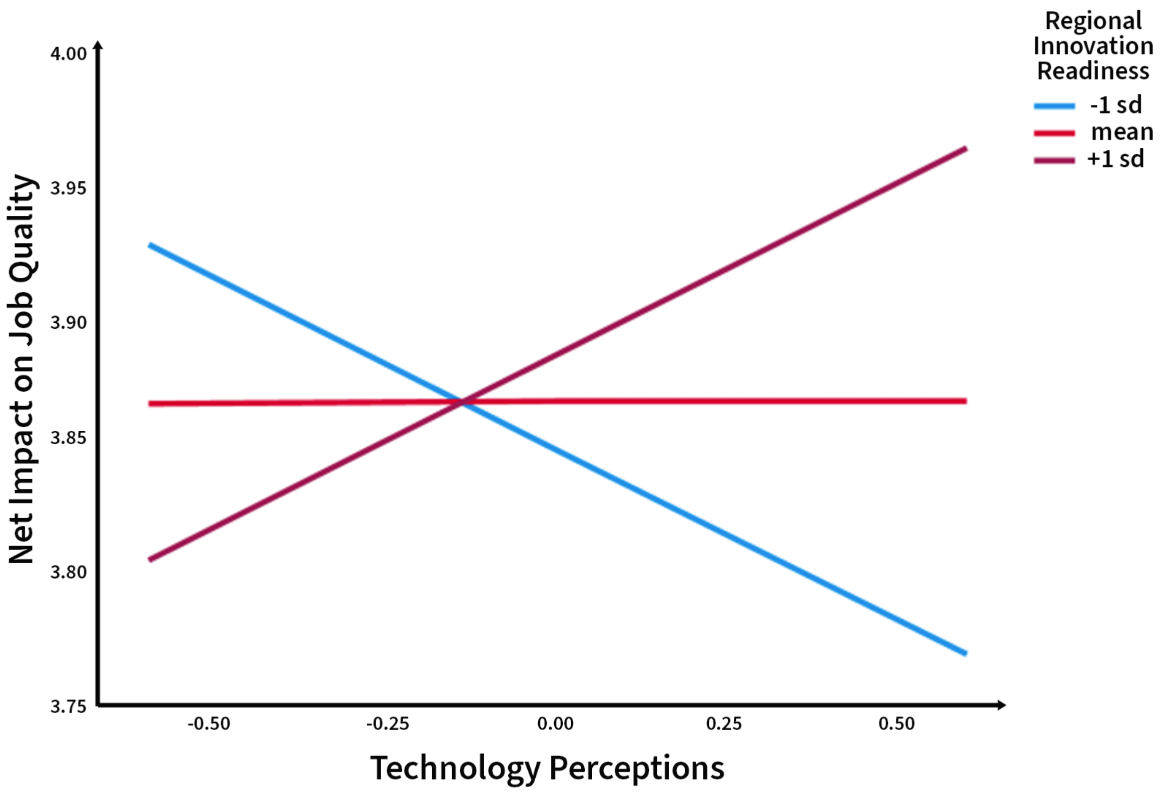


Figure 3d

Net Impact of Technology Perception on Job Quality, moderated by Regional Innovation Readiness



In model 4, we examine the Net Impact on Skills. The overall model is statistically significant (R-squared .097, p<.001), and the Index of Moderated Mediation is .355. The bootstrapped 95% confidence interval for this effect does not include zero (BootLLCI .017; BootULCI .731) supporting the hypothesised moderated mediating relationship. We observe a significant moderation effect for Regional Innovation Readiness (.983, p<.05), which is depicted graphically in Figure 3c. There is a significant difference between the slopes for different levels of readiness. This supports hypothesis 7. We also observe a statistically significant interaction between Perceptions of Technology and HRM (F 5.418, p<.05) which **offers further support for hypothesis 8.**

In model 5, we examine the impact of technology on overall Job Quality. The overall model is statistically significant (R-squared .100, p<.001) and the Index of Moderated Mediation is .458, with the bootstrapped confidence interval estimates not including zero (BootLLCI .100; BootULCI .797). The estimates in this model are interesting because we observe more sectoral differences than in any of the other outcomes. The coefficients for the sectors Electricity, Gas, Steam and Air Conditioning Supplies (-.996, p<.001), Administrative and Support Services (-.668, p<.05), and Education (-.668, p<.05) are negative and significant, and for Construction (-.409, p<.1), Information and Communication (-.348, p<.1), and Professional, Scientific and Technical Activities (-.397, p<.1) are negative and marginally significant. The increased number of statistically significant coefficients suggests greater sectoral variation with respect to the impact of AI on job quality outcomes.

There is a positive direct effect between HRM and job quality (.225, p<.01), which is statistically significant. There is also a significant interaction effect between technology and HRM on job quality (F 4.282, p<.05), **supporting hypothesis 8**. There is also a statistically significant interaction between Technology and Regional Innovation Readiness (1.269, p<.01), **which supports hypothesis 7**. The simple slopes analysis is depicted in Figure 3d. Here the results are striking in that when Regional Innovation Readiness is below the mean, the association between Perceptions of Technology and the outcome of Job Quality is negative, while when readiness is high, this relationship is positive.

Summarizing these results, we find all four of our outcome models are statistically significant, with support for the moderated mediation model, in which Regional Innovation Readiness and HRM both significantly interact with Technology Perceptions in adopting firms. **This supports our hypotheses that these two sets of variables, HRM and Regional Innovation Readiness, are significant moderators of the association between AI adoption and work outcomes.**

5. Discussion of results

There is a long history of research on the adoption and diffusion of new technologies which indicates many potential downsides of any form of technology automation: loss of control over the pace of work undermining physical and mental wellbeing (Ettlie, 1986; Friedland & Barton, 1975); jobs becoming more routine (Brod, 1988); workers subjected to even closer supervision (Mankin, 1983); and disrupted social relations (Nussbaum, 1980). However, we are still learning whether, or when, AI may have a positive or negative impact on important work outcomes. In this study, we contribute to this discussion.

We have extended analysis of the impacts of AI adoption in multiple ways. First, we have considered multiple outcomes, including job quality, in addition to the net impact on jobs, positions and skills. We have also explored positive as well as negative impacts on these diverse work outcomes. Second, we have provided evidence for contingencies which moderate the relationship between technology adoption and these outcomes. This evidence is not only relevant to advancing our theoretical understanding but has significant practical, policy-related implications.

Thirty years ago, in the context of extensive expansion in computerisation, Mirvis and colleagues suggested that "working people in general have many reasons to approach computerised technology with a positive attitude" (Mirvis et al., 1991, p.123). Much more recently, after reviewing a number of real-world case studies, Davenport and Miller (2022) conclude that AI tends to augment rather than fully automate jobs, and that it doesn't appear to be resulting in job losses. The 2023 OECD Employment Outlook report states that "So far, there is little evidence of significant negative employment effects due to AI" (OECD, 2023, Chapter 3, 'Key findings').

Despite the debate over the direction of impacts of new AI technologies on the labour market, history tells us that technology alone does not determine outcomes for work and workers (e.g., Barley, 1986; Thomas, 1994). What becomes very clear as we move from literature which treats technology as objective and fixed, towards a more socially constructed view (Orlikowski, 2009) is that neither the implementation of technology nor its impacts on jobs, work and workers (Barley 1986; 2020) are deterministic but are themselves a function of managerial and social choice (Trist, 1980). Our results support this perspective and add evidence for the role of HRM in driving the cognitions which impact technology adoption decisions.

This study builds on and extends the Technology Acceptance Model (TAM) and the Technology-Organisation-Environment (TOE) perspective, by placing perceptions of technology at the heart of the process between organisational and environmental factors and the decision to adopt AI. Work using the TAM has not pursued analysis of the antecedents to the perceptions hypothesised to drive adoption. We provide a theoretical account of how High Involvement HRM can influence these perceptions. This also extends our current understanding of how HRM practices may be a significant influence on organisational innovation and adaptation, by linking those practices with perceptions of the attractiveness of AI. One of our contributions is to provide evidence that technology perceptions are significantly and positively associated with an organisation's investments in its human resources, in the shape of High Involvement HR philosophy and associated HR practices. Furthermore, we demonstrate that perceptions of technology mediate the relationship between HRM and technology adoption. These relationships hold even after including other significant organisational and environmental variables. This study therefore also extends our understanding of the strategic contributions which HRM makes to organisational-level measures of performance (Huselid, 1995) — in this case, the role it plays in technology adoption, which has previously received limited attention (e.g., Hayton, 2005).

This study also extends the TOE framework, by moving from a model which treats all three categories, technology factors, organisational factors, and environmental factors, as having equal causal priority to treating technology as a perceptual variable which mediates the impacts of organisational and environmental factors. The final model that we analyse represents a synthesis of the DOI, TAM and TOE frameworks, treating AI adoption as a process in which subjective perceptions of technology are taken to be the central mechanism.

Holm and Lorenz (2022) note that the impact of AI on skills depends upon the nature of the application. It has a positive impact on skills where the AI is used to augment work via the provision of information to a job holder for further action. It has a negative impact on skills where AI automates significant tasks and thereby leads to the job holder taking instructions, orders or directions from the AI system. Our results suggest that choice about whether to disrupt or complement human labour is significantly influenced by two factors. First, the external environment in which the organisation operates. Our concept of Regional Innovation Readiness suggests that the environment provides a set of enabling resources that organisations are incentivised to draw upon. We hypothesised that when these resources are available, they create economic incentives to implement AI in ways which create jobs and positions, add to skills demands, and enhance job quality. On the other hand, the absence of those enabling resources serves as a contingency which reduces the likelihood that new jobs and skill demands are created. The most extreme result in this study suggests that when Regional Innovation Readiness is significantly below average, AI adoption is more likely to exert a negative impact on the quality of jobs.

This result has major policy implications. As with many other countries, in the UK a chief political and social concern lies with the observed regional inequalities with respect to wealth and inclusion (e.g., McCann, 2020). Often there are concomitant demographic inequalities along with geographic ones. Policymakers are naturally concerned that the latest round of technological change may further exacerbate these inequalities. The evidence presented here suggests that this outcome may be very likely without interventions, most likely by the state or local governments. The study also suggests that one important avenue is further building regional innovation readiness, through investments in education and connectivity infrastructure. Without such investments, our results suggest that it is likely that AI adoption in low-readiness regions will be particularly detrimental to job quality. Furthermore, if the goal is to increase the number of jobs and raise skill levels across the workforce, then the evidence suggests that readiness levels significantly above current averages are needed.

The second aspect that we have examined in this study is the role played by an organisation's HR philosophy and practices in both adoption and implementation. We show that not only can High Involvement HRM be expected to impact the successful identification, selection, adoption, and implementation of new technologies, but that this orientation also moderates the impact of technology adoption on work outcomes. Prior theories such as the sociotechnical systems theory, have suggested that the involvement of employees as stakeholders, their development and their participation through information or consultation, tends to exert a positive influence upon the outcomes of technology adoption both for employees and for the organisation in terms of a successful process (Trist, 1980). In this study, we apply this insight and examine the contribution of a core set of HRM practices to understanding the role it plays in AI adoption. The current study adds new evidence to this discussion with quantitative evidence in support of prior qualitative studies (Guest et al., 2022).

There is evidence that in many cases, new technologies can enhance job quality. For example, by improving access to data and information and communication, creating new activities, and simplifying interactions between colleagues, use of the internet can increase job satisfaction (e.g., Castellacci & Viñas-Bardolet, 2019; Martin & Omrani, 2015). Often, the positive effect is driven by increases in productivity, job satisfaction and perceived meaning of work, as low-value menial, routine tasks are phased out. In an earlier example of IT adoption, Buchanan & Boddy (1982) show how the introduction of word processing technologies expanded the range of tasks for secretarial staff. This is not to say that outcomes are always positive. There are also potential negative impacts associated with changes in time use and increased stress from digitalisation (Castellacci & Tveito, 2018; Johnson et al., 2020). We extend these prior observations to show that positive outcomes for job quality are contingent upon both HRM philosophy and practices, and the presence of enabling resources in the organisational environment.

An unexpected finding is that organisational size was not significant for the adoption of AI for cognitive tasks. Both large and small firms appear to be willing and able to adopt the technology. This may reflect the relative ease of integration with existing processes for cognitive as opposed to physical tasks. Piecemeal adoption of new technologies in production facilities can be challenging. This effect may be less significant for cognitive tasks. If so, this unexpected finding may carry significant implications for the rapid diffusion of AI technologies across the entire economy. In combination with the findings concerning the impacts on job quality for regions with lower readiness scores, this observation raises the stakes for policymakers.

This study is not without its limitations. Specifically, the survey design is cross-sectional and thus any implied causality needs to be treated as speculative. Future research taking a longitudinal approach with different measurement strategies would be beneficial. A second limitation is that the sample is non-representative. Given the desire to study the impacts of adoption, we decided to weight the sample towards larger firms, by stratifying the sample by size. Setting aside the finding that size plays a more limited role than expected in adoption, our sampling strategy would potentially lead to a higher rate of adoption for the sample versus the population. However, by including more adopting firms, it enables us to examine the dynamics and outcomes of adoption more readily. A final possible criticism is that this study pre-dates the public availability of the most recent generation of generative AI such as ChatGPT. Unfortunately, our data collection was completed within a few weeks of the launch of ChatGPT and so we are unable to determine the impacts – which likely are just now emerging in practice. Future research might benefit from a study focused purely on the effects of this particular technology.

6. Conclusions

We do not doubt the disruptive power of AI for displacing and substantially changing jobs and occupations. However, we also believe that an important step in understanding and creating a humane future of work is to look at how AI is impacting the decisions of organisational leaders today, and how their decisions to adopt AI are impacting the work of today.

By understanding the mechanisms influencing the decision to adopt these new technologies, and how choices about implementation are made, we have a better chance of creating a positive future.

This study contributes to the view that, in reality, both positive and negative outcomes occur as a result of AI adoption. The technology itself is not completely deterministic for impacts on jobs, skills and job quality. Management philosophy with respect to human resources, in combination with the enabling resources in the environment, matter for adopting technology in ways that can enhance positive outcomes.

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The Pissarides Review into the Future of Work and Wellbeing

Automation technologies are transforming work, society and the economy in the UK in ways comparable to the Industrial Revolution. The adoption of these technologies has accelerated through the COVID-19 pandemic, and the impact of automation is unevenly distributed, with a disproportionate impact on demographic groups in lower pay jobs.

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If you have a professional or research interest in the subject of the impact of automation technologies on work and wellbeing and have insights to share, please contact Abby Gilbert, Director of Praxis at the Institute for the Future of Work at abby@ifow.org

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