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Artificial Intelligence (AI) in rural business: The drivers and effects on AI adoption in rural SMEs

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ABSTRACT

This paper investigates drivers of Artificial Intelligence (AI) adoption, specifically in rural small and medium-sized enterprises (SMEs). Research on AI has gained traction in recent times, however, remains an area in need of further investigation, notably the adoption of AI by SMEs, and particularly among rural SMEs. The focus on SMEs is important as they account for the majority of businesses worldwide, playing an important role in job creation and economic development. The research uses secondary data from the Longitudinal Survey for Small Business (LSBS), a large UK panel survey of SMEs, which provides a broad range of variables on a range of SMEs. Probit regression, using a series of environment, firm and network engagement factors as predictive variables, identifies drivers of AI adoption for rural SMEs. Among the numerous drivers of AI adoption in rural SMEs, networking, is identified as a key variable associated with adoption. This research contributes to the limited knowledge on this subject and more broadly to technology adoption in organisations. This leads to policy recommendations in promoting AI adoption among rural SMEs through better communication of the advantages of adoption among SMEs and network development.

1. Introduction

The purpose of this paper is to investigate drivers of Artificial Intelligence (AI) adoption, specifically in rural small and medium-sized enterprises (SMEs). Research on AI has gained traction in recent times, however, it remains an area for further investigation, notably the adoption of AI by SMEs, and particularly among rural SMEs, which has seen very limited research. The adoption of digital technologies, such as AI, has transformed business processes and strategies, but as yet remains distant among many SMEs, and could therefore cause SMEs to lag larger businesses (Wei and Pardo, 2022). The UK Government's AI Opportunities Action Plan (DSIT, 2025) in aiming to establish the UK as a global AI leader is urban-centric, where the plan focusses on growth zones and urban infrastructure which risks exacerbating the rural-urban AI adoption divide. Indeed, rural SMEs are more likely to be impacted by limited resources from their rural location (Korsgaard et al., 2021), struggle with resources dynamism (recent technologies), community dynamics (e.g. community level learning) and resource supply (e.g. suppliers) (Clauss et al., 2022), and tend to have limited technology adoption (Morris et al., 2017). Despite this, digital technologies offer SMEs opportunities to integrate AI into their business processes, which enables businesses to evolve through learning from data and adapting to the environment (Wei and Pardo, 2022). Bowen and Morris (2024) note that digital technologies can provide rural SMEs with a range of opportunities, but the full potential is not being realised from these opportunities.

The focus on SMEs is important as they account for the majority of businesses worldwide and play an important role in job creation and global economic development (World Bank, 2020). Recently challenging economic conditions through multifaceted crises have had a prominent impact on SMEs and influenced these SMEs to seek innovation, most notably the after-effects of Covid-19, disruptions to global supply chains, climate change effects, and Brexit (Dowell et al., 2023). Additional impacts are seen through the war in Ukraine and cost of living crisis, which are felt across many countries around the world. The adoption of emerging technologies, such as AI, has made a considerable contribution to the ability for SMEs to overcome these challenges, as well as collaborate with business partners and optimise business performance (Ghobakhloo and Ching, 2019). Indeed, the emergence of AI has provided SMEs with opportunities to modernise their operations,

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boost productivity, increase efficiency, and develop greater competitiveness in a fragmented business environment (Shukla and Taneja, 2024). Thus, the impact of these economic crises on the adoption of AI among SMEs merits further investigation.

This research investigates the adoption and use of AI in rural SMEs, leading to three research questions on the drivers to AI adoption, as well as the factors thar influence this.

RQ1: *are rural SMEs adopting AI*?
RQ2: *what are the key drivers of AI adoption among rural* SMEs?
RQ3: *how do these drivers influence AI adoption among rural SMEs?*

The paper is structured initially around a literature review that discusses AI and technology adoption among rural SMEs, including specific issues that relate to AI adoption, and the discussion of the conceptual foundations for this research, before the quantitative methodology of this study is outlined in section 3. The findings are presented in section 4, and then discussed in section 5, leading to the conclusions and implications of this research in the final section.

2. Literature background: AI, SME and rurality

AI has its discontents, with jobs threatened as automation driven by this technology grows, potentially resulting in economic inequality (Korinek and Stiglitz, 2021). AI can destroy, replace and generate new products (Lazzeretti et al., 2023), within both the inequality and AI abilities research there is a latent opportunity for rural SMEs to adopt, with an emphasis on regional innovation policy to help deliver adoption (Lazzeretti et al., 2023). But what is AI? This is somewhat contentious, as there are differences in interpretation between academic researchers and policymakers on the definition, conceptual domain and endless abilities of AI (Krafft et al., 2020). The OECD offers five value-based principles and recommendations for policy makers, based on their definition: "*An AI system is a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy*'. A more refined definition is that of the World Bank: '*Artificial Intelligence (AI) refers to the cognitive ability of machine agents that mimics human cognition in processing information and executing tasks for which the machine agent is trained*'. Notably, both the OECD and World Bank issue warnings for AI use and adoption, yet both indicate the vast potential of the technology.

2.1. SME technology adoption

Technologies such as the Internet of Things (IoT), cloud computing, and Smart Systems (SSs) have become an important focus for industry, especially in the manufacturing and retail sectors (Schmidt et al., 2022). Literature on technology adoption among SMEs covers various aspects, including e-commerce (cf. Elia et al., 2021), social media (cf. Setkute and Dibb, 2022), and digital technologies, such as AI (cf. Baabdullah et al., 2021). Adopting digital technologies, such as AI, allows businesses to transform their processes and strategies, which are often lacking among SMEs (Wei and Pardo, 2022). Furthermore, the adoption of smart systems and AI technology can not only improve organisation processes and strategies, but they can also improve supply chain integration and efficiencies (Schmidt et al., 2022). Technology adoption is evident across various stages of entrepreneurship (Cunningham et al., 2022) as digital technologies provide businesses with opportunities and solutions in operations and decision-making processes whilst developing the adaptability of the business (Beliaeva et al., 2020; Ngoasong, 2017). Research has increasingly seen that digital technology can promote innovative strategies and entrepreneurial opportunities for SMEs (Kraus et al., 2019; Sahut et al., 2021). Cutting edge technologies, such as AI, can enhance entrepreneurial opportunities through more developed digital operations, or optimised structures (Jawad et al., 2021), however, Bowen and Morris (2024) concluded that rural SMEs were not taking full advantage of these opportunities.

Despite the opportunities derived from technology adoption, the rate of adoption of AI has been slower among SMEs (Horváth and Szabó, 2019). Challenges exist in enabling AI adoption among SMEs (Rauch et al., 2019), notably access to financial resources. Furthermore, in their research on antecedents to AI practices by B2B SMEs in Saudi Arabia, Baabdullah et al. (2021) pointed to AI technology road mapping, professional expertise and attitudes towards AI adoption as key enablers, as well as the readiness of the SME to adopt, which is determined by its access to infrastructure, its technicality, and awareness to AI adoption. Literature suggests that technology adoption is added if the end user is involved in the early stages of the technology developed (Mishra et al., 2014). This is particularly true for decision support systems where utilising the end user creates tailored technology rather than general tools. It is important to consider this factor when considering AI adoption where it is unlikely that the end user is involved in the development.

Thus, more research is needed in exploring the drivers of AI adoption among SMEs in different contexts, and particularly in exploring macro-environmental factors, including culture, government regulations, national technological advancement level, and the economic situation. The technology is an interesting proposition in that it may influence numerous areas of an SME, may have a great impact on operations, however, it is, relatively speaking, an incremental innovation as any SME with the internet has extant access.

2.2. Rural SMEs contextual challenges and opportunities

Rural SMEs are acknowledged within the literature as facing increased challenges compared to their urban counterparts (e.g. Cowling and Brown, 2024), largely due to less access to resources, however these can be overcome through collaboration (Korsgaard et al., 2021). Indeed, a lack of resources is seen to inhibit entrepreneurial businesses from surviving, growing or innovating (Senyard et al., 2014; Clauss et al., 2022). Morris et al. (2017) noted limited technology adoption among rural agricultural SMEs, highlighting remoteness, socio-economic issues of limited resources, a lack of infrastructure (notably broadband access and speed), unfavorable economic conditions (including Brexit), and uncertainty through policy interventions, notably a drive towards a green economy, as hindrances to technology adoption. Furthermore, Bowen and Morris (2019) underline that limited resource allocation leads to rural SMEs being more passive towards opportunities for growth. Similarly, rural SMEs were observed as not exploiting the full potential of adopting digital technologies, including AI adoption (Bowen and Morris, 2024).

Recent studies have underlined the challenges that SMEs have experienced through a series of simultaneous crises, particularly since the Covid-19 pandemic. Utete and Zhou (2024) discussed the range of effects that rural SMEs experienced during the pandemic. These are varied and include financial issues, such as limited financial resources both from the business and consumer perspective; human resource issues with limited access to staff; infrastructure issues, including limited resources, communication challenges, transport issues and technological challenges; and social issues, including less opportunities to network, poor economies of scale, and a changing competitive environment. Further, rural SMEs face challenges getting finance, but do get favorable interest rates (Cowling and Brown, 2024), so perseverance can lead to better outcomes despite the lack of rural infrastructure. Dowell et al. (2023) pointed to a series of crises multifaceted by nature facing UK-based SMEs in the post-Covid period, with Brexit and climate change also discussed as challenges for businesses, including discussions of increased costs on the business. Indeed, non-urban business often face a paradox between sustainability regulations, and issues such as transport which are magnified in regional settings. This centralizes the regional economic and sustainability arguments for businesses (Öberg and Aronsson, 2022). Given the resource constraints of rural SMEs, they face greater challenges in overcoming such crises and are less likely in developing resilience and increasing competitiveness. As such concerns are raised regarding the Government AI Opportunities Action Plan (DSIT, 2025) which seems to largely ignore the UK's rural areas and is focused on growth and opportunities from an urban centric perspective.

In rural and regional areas, relationships and networks provide an area which SMEs can develop to compete and succeed (Dowell et al., 2015). It has been argued that a lack of networks and ability to 'share' and 'learn' is a significant disadvantage to rural SMEs, a factor leading to the liability of rurality (Clauss et al., 2022). That said, collaboration amongst SMEs can induce turnover growth via reciprocity and innovation (Brink, 2017), indeed the ability to collaborate has an impact on a business' ability to survive, which was highlighted during the Covid-19 pandemic (Gupta et al., 2024). The use of networks can drive rural SME business growth directly, but also indirectly via innovation adoptions (Tuitjer and Küpper, 2022). Arguably the ability to use networks is an imperative aspect for rural SMEs' survival, growth, and innovativeness. Thus, given the challenges rural SMEs face, the opportunities developed from networks, and the promise of AI investigation is necessary.

AI adoption requires money, and having good resources to invest is a developed antecedent of AI adoption (Bettoni et al., 2021). Access to finance has long been argued and researched as an antecedent of innovative practice. The availability of credit is an essential factor in SME innovation (Lee et al., 2015). Financial constraints are a key issue leading to lower levels of innovation in SMEs. Indeed, the propensity to innovate is sensitive to the SMEs' financial health (Brancati, 2015). It has also been argued that while AI software is accessible, the cost of adoption in terms of new IT infrastructure, systems and staff development are all costly, meaning AI is not inexpensive to implement for SMEs (Cooper, 2025). However, there are some opportunities to be gained from AI adoption.

There is something to gain from the adoption of AI in SMEs (Mills, 2019), such as enhanced productivity (Carayannis et al., 2024) and the transformation of business practices (Wei and Pardo, 2022). SMEs can better understand and manage cash flows, incoming and outgoing, and become more attractive to lenders who can better estimate risks (Mills, 2019). This can then lead to rural SMEs advantages in terms of lower interest rates borrowings (Cowling and Brown, 2024). As such, rural SMEs can develop a windfall from AI deployment. AI can also be used to develop revenue growth for small firms (Kumar et al., 2024). There are also marketing related benefits to which SMEs can gain from the use of AI (Wei and Pardo, 2022), despite the known downsides of AI.

2.3. Discussion of factors which contribute to AI adoption

Given the liability of rurality (Clauss et al., 2022) and the potential of AI for SMEs (Kumar et al., 2024; Mills, 2019) the need to understand what drives AI adoption is an imperative. The antecedents of technology, and AI adoption can be grouped into three areas, namely environment (exogenous shocks), firm (internal) and network factors. For the most part, the environment and firm factors act as control variables, while network participation is an area which more policy and SME level interventions can be actioned. In order to address the first research question, and develop the others, we set out here to understand what may influence adoption of AI in rural SMEs.

Environmental factors in which the organisation operates have been linked to AI adoption in prior research on SMEs (Badghish and Soomro, 2024). Environment factors relate to multifaceted crises that SMEs have faced in recent years, particularly in the post-Covid period (Dowell et al., 2023; Utete and Zhou, 2024). This includes the negative impacts seen to SMEs in relation to Brexit, the impacts of the Covid-19 pandemic on SMEs, as well as impacts of climate change, which bring opportunities to SMEs in exploring more sustainable practice (Dowell et al., 2023). The various disruptions have caused uncertainty in regional SMEs, with the global financial crisis, Brexit and Covid-19 all contributing to a new normal of uncertainty requiring SME resilience (Brown and Roy, 2020). All of these affect cash reserves, the ability to function, customers, supply chains, and many other aspects of the SME in rural locations, and this would arguably influence the adoption of AI as a saviour, or perhaps push back the decision to adopt.

Brexit was perceived as a major constraint and obstacle for SMEs, and in particular many SMEs were holding back on innovation (Brown et al., 2019). SMEs strategic decisions were broadly and negatively affected by Brexit, and the decisions around innovation were seen to be less likely (Brown and Roy, 2020). Moreover, Brexit has also been found to have a regional skew, with some regions less resilient and more scarred by the process of withdrawal from the EU (Cowling and Brown, 2024). One effect of Brexit is on labour shortages in rural areas and sectors, with a large disturbance to the food and farming sector (Yarwood et al., 2023).

The impact of Covid-19 was global, with the pandemic impacting upon health and economies seeing increased unemployment and detrimental effects on sectors such as tourism (Beckman and Countryman, 2021). Uncertainty about all aspects of the Covid-19 pandemic – the economic recovery, economic policy, shifts in working patterns, and shifts in consumer spending habits all create an unsettled environment (Altig et al., 2020). Covid had numerous effects, limiting strategic decision making, reducing financing abilities and operations for SMEs (Clauss et al., 2022). Yet studies have found that innovation with processes is essential and digital innovation is a key element for SME progression and survivability in a post-Covid environment (Caballero-Morales, 2021). Thus, given the confounding research, we may expect an effect of Covid on the adoption of AI.

Sustainability is an area which has been the focus of a great deal of academic and policymaker attention. SMEs innovate differently to larger organisations, and a sustainability orientation when innovating is also this way (Klewitz and Hansen, 2014). There is evidence that much of the innovation in SMEs is developed with a sustainability lens, thus innovation with emphasis on the environment (Klewitz and Hansen, 2014). This may be a process innovation, to create less pollution, for example. This would be aimed at protecting future generations, and less detrimental to the green environment.

H1. *Environmental factors will influence rural SME AI adoption*

Firm factors relate to literature on firm-specific drivers to AI adoption (Baabdullah et al., 2021). These include the readiness of the firm to adopting AI technology, AI technology road mapping, professional expertise and the attitude of the firm to AI adoption,. Firm factors include the ability of the firm to use AI adoption to develop greater strategic and entrepreneurial practice (Kraus et al., 2019; Sahut et al., 2021). The adoption of AI, indeed any technology, will require strategic thinking and decision making.

Having an innovative culture, innovative processes can lead to adoption and innovation (Prasanna et al., 2019). The use of prior knowledge helps the innovation process; thus, innovation predicts innovation, in particular incremental innovation (Choi and McNamara, 2018). Innovation may be attributed to the experience of the people within the organisation and the workplace cultures and their internal communications (Monge et al., 1992). To develop capacity, to move beyond issues facing and disrupting the business having an entrepreneurial orientation is an imperative (Zighan et al., 2022). In short, organisational culture, and the ability to adapt this, is a driver of AI adoption (Bettoni et al., 2021).

H2. *Firm level factors will influence rural SME AI adoption*

Finally, the network factor looks at the positive role of networks in effecting AI adoption (Korsgaard et al., 2021; Utete and Zhou, 2024). This is at times referred to as the social capital approach, where networks are used to meet challenges and to innovate (Prasanna et al., 2019). Electronic integration and communication amongst organisations in rural and regional areas is essential to help develop mutually beneficial outcomes and overcome issues associated with geographic isolation (Steinfield et al., 2012). In rural areas SMEs will be part of various networks: social, informational, production, and markets to name some (Filippini et al., 2020). Indeed, social networks have been found as an antecedent of technology and practice adoption, where knowledge is shared and co-created, and conformity, to an extent, can take place (Cheng, 2010). Within SMEs, gaps in knowledge are identified, and the network is used to ease these gaps, leading to innovative behaviors (Deja et al., 2023). Essentially, collaboration via networks helps SMEs in rural areas to access resources needed to innovate and digitize (Beckmann et al., 2023). Thus, we anticipate that network engagement will be a factor driving the adoption of AI, as it is seen to close gaps, aiding innovation and practice in rural SMEs.

H3. *Network engagement will influence rural SME AI adoption*

Following the development of the concepts outlined above, Fig. 1 presents the conceptual framework for this research, outlining the antecedents to AI technology adoption drawn from the literature. These are structured around environment-based factors, which consider the economic environment in which rural SMEs operate; firm-based factors, which look at the firm's strategy and previous innovation activity; and network-based factors, specifically, the ways in which the SMEs have engaged or sought to engage in networking activities.

3. Methodology

Having identified the research questions and subsequent conceptual framework, this research adopts a quantitative methodology, in which secondary data analysis is used to develop insight. The methodological approach utilises the Longitudinal Survey for Small Business (LSBS), a large United Kingdom (UK) survey of small business, which provides a broad range of variables on a range of SMEs. The analysis uses a binary probit owing to the nature of the dependent variable and the type of investigation. Measures were developed from the existing items in the survey, to create proxy measure to address the research questions, and test the conceptual model.

3.1. Data

The Longitudinal Small Business Survey (LSBS) has been conducted each year since 2015 within the UK. The data covers significant events, including Brexit (Brown et al., 2019) and the Covid-19 pandemic (Brown and Roy, 2020), as well as the cost related issues/crisis (Dowell et al., 2024). Each of these major events has sociological and economic effects on SMEs in rural areas and, importantly, events such as these have been found to cause uneven impacts across regions (for example, see Brown and Cowling, 2021). Yet, each event may be thwarted for SMEs by climate change (Hampton et al., 2023). The LSBS canvasses each of these issues, in addition to the adoption of AI technology amongst other firm level data collected on SMEs. The survey is undertaken with SMEs which comprise of less than 250 employees, regardless of turnover and assets, and includes microbusinesses and those that do not have more than one employee.

3.2. Analytic method

The research questions and conceptual model require regression analysis, as the cause-effect relationship is the central consideration of this research. A binary response can be the presence or non-presence of something, purchase or non-purchase, and binary regression allows researchers to see how a set of predictor variables are related to this dichotomous variable (Harrell, 2015). In a binary model (including probit), the dependent variable takes the values of zero and one (Horowitz and Savin, 2001), in this case, zero represents non-adoption of AI and one represents the adoption of AI. In both cases this is rural SMEs only, as this is what the conceptualised model dictates. In a binary probit the probability that the dependent variable is one (that is an AI user) is a function of explanatory variables (Horowitz and Savin, 2001). For this research, there are a series of probit models to test the proposed conceptual model. One is estimated for each of the components of the conceptual model, and another final estimate which integrates each explanatory variable included. Control variables are also included in each. The probits are conducted in accordance with good practice (Hoetker, 2007) and have prior use in SME based research (Kuo and Li, 2003) and innovation in SMEs (Radicic and Petković, 2023). The probit estimate equations are briefly outlined in Appendix 1.

The dependent variable is binary (0/1) with rural non-adoption of AI (=0) and rural adopters of AI (=1). This measure was taken from the then most recent survey wave (year 2023), where all respondents included were asked the question about AI. Respondents were asked if they have adopted AI in the past 12-month period in the final wave of

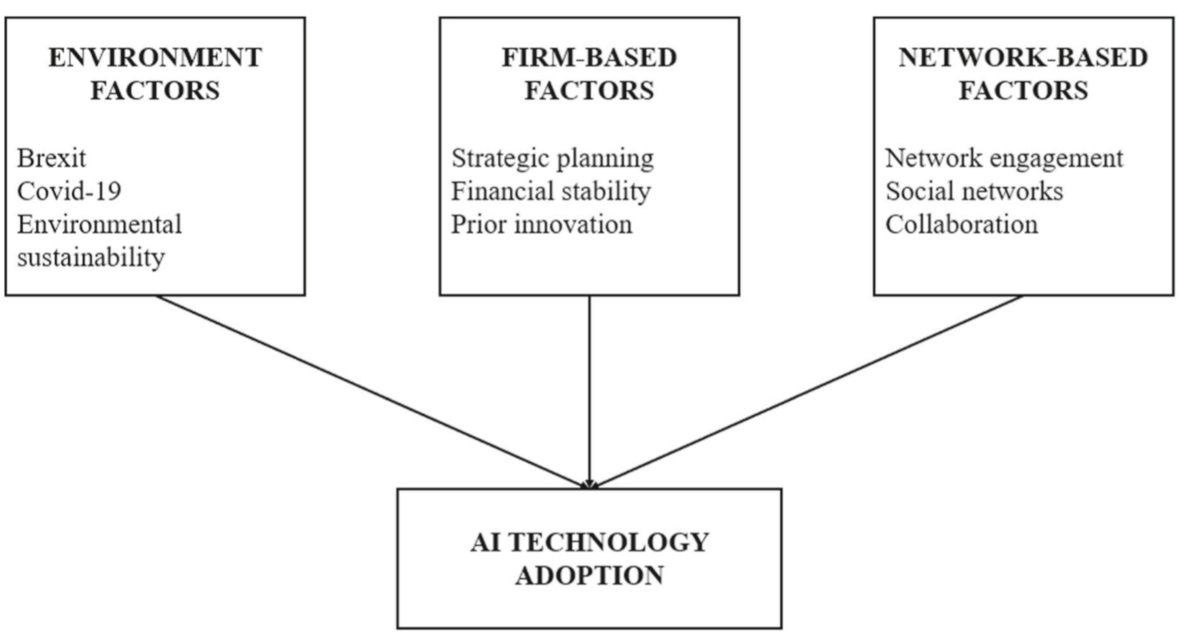

Fig. 1. Conceptual framework.

analysis. Prior waves of measurement had restricted coverage of AI in rural SMEs, thus making panel regression, such as fixed effects and random effects unsuitable, as we are only able to use one wave of AI adoption, that being the final wave available at the time of analysis for the dependent variable.

The predictive variables were each drawn from prior waves of the survey, thus temporal order exists based upon the year that the data collection was undertaken, giving a sequence of independent and outcome variables. For environmental factors, three variables were included to measure Brexit, Covid-19 and green sustainability. Four variables were included to measure firm factors, business strategy (planning), finances, process innovation, and goods/services innovations. Network involvement, the final area, was measured using a single measure. Additionally, firm size, firm age, access to finance and sector are included as a control variables (sector, SME size and SME finance seeking), which have prior links to AI adoption in SMEs (Schwaeke et al., 2025).

Brexit and Covid-19 are developed from a series of items related to the topics. These were not scales, rather a series of items that spoke to impact of the event(s). Both contain a series of items which measure the effects on the SME. Brexit items examined the impact on planning and operations, with eight (8) binary no/yes options. Covid also contained eight (8) items which were binary response gauging the effect of Covid on plans and operations. In both cases a sum of each item was used. Green sustainability is a single item, where respondents were asked about the impact of climate change on their SME and if they consider it in decision making, with never, sometimes and always the given response categories.

Strategic planning is a single item measurement. Strategic planning was measured using business planning, with respondents asked if they kept a formal business plan. Innovation took the form of two measures, one for goods and service and the other for process. These measures were binary, with respondents indicating if they had past engagement with goods/services innovation and also process innovation.

Network engagement is defined as obtaining information (and resources) for the SME from external contacts (Ferreira et al., 2022). In the LSBS an exhaustive range of contacts are included, and a binary measure of engagement, to seek information (resources) from external sources, which encapsulate any engagement, and is used here. The variables included are summarised in Table 1.

4. Findings

This section presents the findings from the quantitative research. Initially, descriptive results for rural AI adopters are presented, before the results of the regression analysis are discussed, leading to the evaluation of the research questions.

4.1. Descriptive results for rural AI adopters

When analysing rural SMEs who have adopted AI, there are a number of significant differences between them and the non-adopters of AI in rural areas (using ANOVA and Chi-square tests for differences). For the full sample, the profile of rural SMEs led to a sample of n = 3040, of which n = 236 had adopted AI (7.86%). The rural adopters were more likely to have employees (86.55% versus 76.98% among non-adopters, $p < 0.001$), and those who had employees on average had more of them (mean = 27.4 versus mean = 15.1 among non-adopters, $p < 0.001$), and a higher percentage intended to increase the number of employees in the coming 12 months (38.24% versus 23.45% among non-adopters, $p < 0.001$). For self-reported turnover, the rural AI adopters had a higher mean (mean = £6,018,563.20 versus mean = £2,241,863.50 among non-adopters, $p < 0.001$). More of the AI adopters were likely to have more than one site (18.10% versus 14.35% among non-adopters, $p < 0.01$) and also have more sites (mean = 1.44 versus Mean = 1.38 among non-adopters, $p < 0.001$). In terms of people, there were no differences between AI adopters and non-adopters for women or minority ethnic ownership/management.

Given the liability of rural (Clauss et al., 2022) and the known issues around the rural digital divide (Morris et al., 2017), there are disparities between urban and rural SMEs. Among urban SMEs in the survey (n = 6452), who have answered the AI question (n = 658), 10.20% have adopted AI. This is a larger rate of adoption than for the rural SMEs (7.83%). Using a Chi-square test, the difference between the rural and urban cohorts is significant ($p < 0.001$). As such, the adoption is lower in rural areas, and given the potential of AI this lack of uptake requires further attention.

Table 1
Variable description.

Variable	Mean	Std. dev.	Min	Max
Brexit	7.944	0.405	1	8
Covid	11.89	0.708	1	12
Sustainability (environment)	2.230	0.716	1	3
Strategic planning	0.393	0.489	0	1
Process innovation	0.208	0.4067	0	1
Good/service innovations	0.329	0.4700	0	1
Network engagement	0.275	0.4467	0	1

(observations based on all variables regression n = 3003).

4.2. Regression results

Each of the four regressions had sound fit qualities, and post-estimate testing indicated robustness. The likelihood ratio chi-square were all significant ($p < 0.001$) meaning the whole 'models' are significant. Robust standard errors were used to enhance the estimates fit properties and accuracy. A Hosmer-Lemeshow goodness of fit test was estimated after each regression, and all indicated a sound fit. There are four regressions (1) environment, (2) firm and (3) network estimates were each made, and a (4) combined regression. Each of these, and the coefficients are reported in Table 2.

The first three regressions were for the parts of the conceptual model. For the environment factors, Brexit had a significant negative effect ($\beta = -0.253$, $p < 0.01$), sustainability (green environment) ($\beta = 0.156$, $p < 0.01$) and Covid were found to be insignificant. Thus, the results indicate Brexit and sustainability/environment as being significant factors, hence we find initial support for push and pull aspects of AI adoption. Firm factors had a series of significant results. Having a business plan ($\beta = 0.2547$, $p < 0.01$) had a significant positive coefficient. In addition to this, a history of innovation was also significant, with process innovation, and goods/services innovation having positive coefficients ($\beta = 0.454$, $\beta = 0.509$, $p < 0.01$ respectively). The results indicate that having a strategically minded innovative past increases the probability of AI adoption. The final unit of analysis was networks, and the seeking of information from any network (formal or informal, etc.) was estimated. The coefficient was found to be significant, and positive ($\beta = 0.347$, $p < 0.01$).

The main analysis is a combined binary probit regression containing predictive variables, environmental factors, firm factors, and networks. The model had sound goodness of fit, confirmed with the Hosmer-Lemeshow test. Brexit had a negative, significant corelation ($\beta = -0.144$, $p < 0.01$). Strategic planning ($\beta = 0.203$, $p < 0.01$), process innovation ($\beta = 0.414$, $p < 0.01$) and goods/services innovation ($\beta = 0.476$, $p < 0.01$) had significant positive coefficients. Networking had a significant positive coefficient ($\beta = 0.168$, $p < 0.05$).

For each of the estimates included in the research, SME size, SME sector, SME age and finance seeking were included as control variables. In each of the estimates, SME size was found to be significant. The sector also had a significant effect in the full estimate, with transport/food/retail/accommodation as well as other services having a negative association (compared with business services as the base). This was repeated across the other estimates. Finance seeking was not significant in any of

Table 2
Regression estimates on rural AI adopters and non-adopters.

Variable	coef (s/e)	p	(coef (s/e)	(p)	coef (s/e)	(p)	coef (s/e)	(p)
Brexit	−0.1438 (0.0746)	0.05	−0.2529 (0.0723)	0.01				
Covid	−0.0345 (0.0316)	0.28	−0.0535 (0.0309)	0.08				
Environment	0.0790 (0.0567)	0.16	0.1558 (0.0527)	0.01				
Strategic plan	0.2033 (0.0760)	0.01			0.2547 (0.0752)	0.01		
Innov process	0.4137 (0.0807)	0.01			0.4543 (0.0792)	0.01		
Innov g/s	0.4761 (0.0761)	0.01			0.5093 (0.0744)	0.01		
Networking	0.1676 (0.0764)	0.03					0.3467 (0.0729)	0.01
Sector:								
Production +	0.0313 (0.0906)	0.73	−0.0406 (0.0858)	0.64	0.0636 (0.0885)	0.47	0.0124 (0.0860)	0.89
Transport +	−0.2932 (0.1011)	0.01	−0.4087 (0.0963)	0.01	−0.3051 (0.0993)	0.01	−0.3656 (0.0962)	0.01
other service	−0.4241 (0.1446)	0.01	−0.4812 (0.1358)	0.01	−0.4384 (0.1437)	0.01	−0.4726 (0.1369)	0.01
Finance	0.0904 (0.0818)	0.27	0.1535 (0.0791)	0.05	0.1401 (0.0804)	0.08	0.1581 (0.0782)	0.04
SME age	0.0126 (0.0390)	0.75	0.0102 (0.0366)	0.78	0.0126 (0.0387)	0.75	0.0188 (0.0365)	0.61
SME size	0.0030 (0.0010)	0.01	0.0046 (0.0009)	0.01	0.0033 (0.0010)	0.01	0.0042 (0.0009)	0.01

(Dependent variable 0 = rural non-adopting SMES, 1 = rural AI adopters.
$p < 0.05$*,$p < 0.01$ **,$p < 0.001$ ***.
Sector base category = business services, key: Production +: production/construction; Transport+: transport retail, food service, accommodation).

the included analysis.

4.3. Conceptual model evaluation

In general, results are broadly consistent with the literature that was used to develop the conceptual model, Table 3. For H1, Brexit was theorised as having a negative effect, and Brexit was found to have a significant negative association with AI adoption. When accounting for all variables in the model, Covid and green environment were not found non-significant. As such, there is partial support that exogenous shocks are pushing SMEs into the adoption of AI. Of greater interest is the firm level variables. Strategic planning was argued to have a positive association, which was supported. Prior innovation, that is SMEs who had previously innovated, were argued to be more likely to adopt, which was supported. Thus, we see support for H2 that firm level factors influence the adoption of AI. Finally, network engagement/seeking information was theorised to influence AI adoption, which was also supported. As such, there is support for H3. Arguably, H3 is the most important as engagement in networks is an area which the SME can control, and policy makers can encourage. Further, there is already existing infrastructure in many places for networks enabling quick diffusion of information about AI and opportunities for rural SMEs to engage.

5. Discussion

Findings from this research provide new insights into AI adoption by SMEs and the variance between urban and rural based SMEs' behaviour and strategies. The systematic review of literature explored the challenges faced by SMEs in terms of technology adoption then focussed on rural SMEs and how they differ from other SMEs. From the extensive literature research, it became apparent that there is a great void in our understanding of SME adoption behaviour and in particular SMEs in the rural context which has had scant academic attention. From the literature review a conceptual model was developed and subsequently investigated in the findings section by analysing the UK Longitudinal Survey for Small Business. This research extends the general literature on AI adoption, in particular by finding that networks play a crucial role. Thus, the research contributes to what is an undeveloped literature on rural AI adoption.

Table 3
Results summary of conceptual model and hypotheses.

Effect on AI adoption	Supported/not
H1: *Environmental factors will influence rural SME AI adoption*	Partial support
H2: *Firm level factors will influence rural SME AI adoption*	Supported
H3: *Network engagement will influence rural SME AI adoption*	Supported

Firstly, addressing research question 1: *are rural SME's adopting AI*? The findings provide evidence that those adopting AI (n = 238, 7.83%) were more likely to have employees, tended to be larger, have more sites and greater turnover than non-adopters. In addition, they were in a position of growth or seeking to grow and had a higher turnover than non-adopters. It could be considered that these businesses are better resourced with a clear strategic growth intention and therefore require greater assistance in decision making. As such, they are more likely to embrace technology due to their needs but also in terms of their size and turnover to justify the necessary technology these being key technology adoption factors in previous literature. That said, the adoption rate is significantly lower than that of urban counterparts.

Moving onto research question 2: *what are the key drivers of AI adoption among rural SMEs?* and RQ3: *how do these drivers influence AI adoption among rural SMEs?* AI adoption in rural SMEs has numerous drivers, the findings provide evidence that networking influences AI adoption. The exogenous factors remain a challenging area for policy makers, and programmes do exist to make firms more strategic, emplacing an innovative culture is more difficult. One key factor which can be encouraged by policymakers is engagement with networks. Networks are an important element of knowledge exchange activities and relationship networks in rural can be used to compete (Dowell et al., 2015). These networks are critical in rural regions where isolation and remoteness are key factors. Rural SMEs are involved in networks for social, informational, production, and market purposes (Filippini et al., 2020).

In the farming context, programmes such as Farming Connect in the UK play a vital role in establishing and maintaining networks whilst utilising events to transfer knowledge via demonstration farms or events based on the latest techniques and technologies. This network collaboration assists rural SMEs to access resources needed to innovate and digitize (Beckmann et al., 2023). Another antecedent is that those with prior innovative activity are more likely to adopt AI. This is a factor backed by this and previous research, where those which are already technologically minded are more likely to embrace further technology. For example, in the dairy sector which has for a long-time embraced data driven decisions and embraced technology, we are now seeing dairy farmers enter a period of robotics and precision farming. As such, AI may be the next step in automation and mechanisation (Korinek and Stiglitz, 2018).

Further antecedents analysed considered the impact of economic crises on the adoption of AI among SMEs. The study focussed on two key occurrences, these being Brexit where the United Kingdom voted to leave the European Union, and the more recent Global Covid-19 pandemic. According to Brown et al. (2019), Brexit is seen as a major constraint on SME innovation. Our study concurs with this notion where the findings signify that Brexit did influence AI adoption by SMEs. While Caballero-Morales (2021) finds that process innovation and digital innovation are key for SME progression and survivability in a post Covid environment (Caballero-Morales, 2021), this study found that Covid had no effect on AI adoption.

There are numerous concerns regarding the impact of AI on jobs and in particular replacing jobs or making some jobs obsolete. Where studies highlight less staff required due to AI adoption (Korinek and Stuglitz, 2021), our findings paint a different picture in the rural context. That being, more staff will be employed due to the adoption of AI. This may be influenced by AI's ability to destroy, replace and generate new products (Lazzeretti et al., 2023), and also to overcome rural and regional inequalities and nurture entrepreneurial opportunities. While some firms acknowledge that there will be certain job losses due to AI adoption, they recognise that AI could create better paid jobs, as such we may witness a shift in the type of jobs available and their numeration. Or we may see organisations adopting AI rather than using expenses agents which in turn helps generate greater profits to reward staff.

Research by Morris et al. (2017) identifies the role of contractors in technology exchange. Where it is not necessarily the farmers who adopt the technology but the contractors who then utilise the technology on numerous farms, thus justifying its potential costs and being skilled on its use. As such this enables the key factors of the Technology Acceptance Model by Davis (1989). This factor requires further investigation in terms of AI where the agricultural contractor could utilise the technology for improved decision making and operations efficiencies, for example, adopting SMART systems as to when to conduct certain farming operations or providing bespoke applications for clients. This could then reduce the lag in digital technology uptake between large and small SMEs, as noted by Wei and Pardo (2022).

6. Conclusion

The objective of this study was to understand antecedents of Artificial Intelligence (AI) adoption, specifically in rural small-to-medium enterprises (SMEs). While digital adoption in rural areas has long been noted as having a dark side (Grimes and Lyons, 1994), and more recently AI and innovation concerns have been highlighted, the role of AI in innovation ecosystems requires thought (Carayannis et al., 2024). Digital transformation has been highlighted as a key for survival, alongside collaboration for business in the turbulent business environment (Gupta et al., 2024). Moreover, in terms of levelling up society, a reduction of inequality and improved innovativeness of regional business is required (Pinheiro et al., 2022). Part of the EU drive to enhance regions innovation is around smart technology adoption to leverage existing capabilities (Balland et al., 2019). This research speaks to these needs, specifically AI adoption. Furthermore, the work provides evidence on the impact of the economic crises on the adoption of AI among SMEs and more broadly technology adoption in the rural context. As previously stated, this research contributes to the limited knowledge on this subject.

Findings from the research underline that engagement in AI adoption has positive intentions, with 48.36% of rural SMEs who had adopted AI expecting to see business growth in the next 12 months, with 86.45% of rural AI adopters aiming to grow sales, and 80.39% expecting to increase the number of employees. Practical implications of the findings could help SME owner/managers to embrace technology adoption and alleviate concerns of the perceived negative impacts of AI technology.

Based on this research there are several policy implications for supporting AI adoption in rural SMEs. Firstly, investing in the rural networking infrastructure and ensure that AI growth zones include rural locations. Research findings point to the value of network engagement in supporting AI adoption in rural SMEs, as higher levels of engagement in networks were observed in SMEs that had adopted AI. For rural SMEs, networks are seen as important in overcoming the lack of spillover effects seen in business parks or clusters. Policy should aim to promote rural business networks, such as the role played by Farming Connect in agriculture and the establishment of AI innovation hubs in rural locations to facilitate knowledge exchange. Funding could be allocated to enhance networking opportunities and support online access for rural SMEs.

Secondly, build digital infrastructure, where rural areas require improved connectivity to make AI adoption feasible. This is also reliant on access to broadband and mobile connectivity in rural areas, and the avoidance of a digital divide. Practical outcomes should aim to facilitate network engagement and promote the benefits of technology adoption among rural SMEs. Finally, findings point to sustainability as a notable antecedent to AI adoption, as SMEs that focussed on sustainability within their strategic thinking were more likely to adopt AI technology. For policymakers, this indicates that sustainability can be woven into broader technology adoption policies, and communicating the value of this to SMEs could lead to practical advantages of AI supporting SMEs in their sustainability goals.

Overall, this research underlines the benefits of AI to rural SMEs, and rural communities, if adopted in a positive manner. Support is required, this may be in the form of targeted financial support that recognise the unique constraints on rural SMEs. The support of networks is important in facilitating this, but technical challenges that are often apparent in rural areas need to be overcome, notably by investing in infrastructure, training, mentoring and networks. Limitations are acknowledged in the research in the breadth of data available through the Longitudinal Small Business Survey, and that future research could look to explore qualitative methods to add depth to understandings of rural SMEs' attitudes to AI technology adoption. Additionally, given the context of the UK, future research that explores different settings would also add value to knowledge on the subject, especially in Global South settings.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Ethical approval and informed consent statements

Ethical approval was granted by the authors' research institutions.

Use of AI

This paper is the work of the authors, and AI has not been used at any stage in the development and writing of the paper.

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CRediT authorship contribution statement

David Dowell: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Validation, Writing – original draft, Writing – review & editing. **Robert Bowen:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Validation, Writing – original draft, Writing – review & editing. **Wyn Morris:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of conflicting interest

There are no conflicts of interest to declare.

Appendix 1. Probit Models

Probit Model:
Pr[Y = 1] = Φ(Xi,•β^)
Where:
Pr [y = 1] is Probability of Y = 1, i.e. probability that the dependent variable = 1.
Φ is the cumulative normal distribution.
Xi is the constant
β^ is the beta weight(s) of the predictive variables.
Model estimate 1: SME environment.
Pr(AI adoption = 1) = Φ(β0 + β1brexit + β2covid+ β3sustainability + β4sme size+ β5finance seeking+ β6sector)
Model estimate 2: SME characteristics.
Pr(AI adoption = 1) = Φ(β0 + β1strategy + β2prior process innovation + β3prior goods/services innovation + β4sme size+ β5finance seeking+ β6sector)
Model estimate 3: Networks.
Pr(AI adoption = 1) = Φ(β0 + β1networks + β2sme size+ β3finance seeking+ β4sector)
Model estimate 4: Full model.
Pr(AI adoption = 1) = Φ(β0 + β1brexit + β2covid+ β3sustainability + β4strategy + β5prior process innovation + β6prior goods/services innovation + β7networks + β8sme size+ β9finance seeking+ β10sector)

Appendix 2

Items included in the research examples.
Have any of these plans (X) been affected by the Coronavirus COVID-19 pandemic?
Whether plans over the next three years have been affected by Brexit X?
Here X is a particular plan, for example - Capital investment.

Data availability

Data used in the paper is from the Longitudinal Small Business Survey, access to which is available upon request from the data holders.

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Data Source

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