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Understanding Artificial Intelligence Adoption and Use in Rural Small Medium Enterprises: An Opportunity to Level Up?

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Understanding Artificial Intelligence Adoption and Use in Rural Small Medium Enterprises: An Opportunity to Level Up?

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ABSTRACT

The growth of artificial intelligence (AI) has posed challenges and yet offers opportunities for SMEs. The adoption and use of AI has been heralded as the 4th Industrial Revolution, however, there are considerations as with most technologies regarding implications for society. The concerns around AI's impact on employment, and industry sectors is parlayed by the urban rural technological divide. This research aims to identify the adoption of AI by rural SMEs, and to understand what if any impact it is having. We conduct analysis to identify which SMEs in rural areas are using AI, and what their future intentions are. Thus, addressing the research needed to understand what, if any, effect AI will have on rural economies in terms of jobs, exporting, and in future extensions. We profile the SMEs who have adopted AI, then analyse why they adopted, along with their future intentions. We find that networks more so than internal factors play a significant role in the adoption of AI. Moreover, the intentions of AI adopters are to expand, and therefore contribute more to rural economies rather than constrain employment for example.

Key words:
Artificial intelligence (AI), rural, small-medium enterprises (SMEs), technology, adoption

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CONTENTS

NON-TECHNICAL SUMMARY

Artificial intelligence (AI) is considered as the 4th Industrial Revolution, or as the Industrial Revolution for human intellect. AI is software that mirrors and produces human like behaviours, responses and decision making. Essentially AI mimics human cognitive functions. AI can scale human intelligence for SME use, as such, AI attracts the attention of SMEs and academics alike.

A sometimes-balanced debate has emerged that there will be gains from AI adoption, in terms of productivity and creativity. However, there will be anticipated losses of jobs to offset the economic and productivity gains. For rural SMEs if the negative were to be true the effects on local economies could be devastating with potential gains offset by lower employment.

There is a known and well researched rural-urban divide in technology access and adoption. This extends into innovation rates, with innovation of process and goods/services lower. Within rural SMEs there is divergence with technology access and use, as well as innovation levels and adoption. The adoption could be limited owing to the digital divide and lesser uptake rates of innovation.

Rural SMEs face substantive issues with regards to location beyond technology. There is a series of confounding macro factors, such as climate change and Brexit which impact upon rural SMEs disproportionately. This calls for smarter operations in areas such as transportation (climate change) and human resource management (Brexit). These are examples and areas in which AI could be advantageous, based on transport allocation and intelligent rostering.

Our findings show that AI use differs between rural and urban based SMEs. However, of more interest is the difference between rural adopters and non-adopters of AI. We identify fundamental differences between the two groups. Our aim is to better understand why some SMEs have adopted AI and why some have not. Essentially the analysis identifies differences between adopters and non-adopters, and analyses what drives the decision to adopt.

In profiling the rural SMEs who have adopted, these tend to exhibit positive intentions, with a higher proportion indicating they expect increased turnover and growth. Interestingly, the SMEs who have adopted are more likely to increase staff levels going forward, more likely to invest in training staff and to have a positive outlook on their strategic future. The

SMEs who have already adopted AI are not looking to reduce staff, nor close sites of operation.

Consistent with prior findings our results indicate that the SMEs who have adopted a new technology, in this case AI, tend to have a larger number of employees and turnover. Thus, in general the results indicate that expansion and development is more likely with AI adopters.

Our findings also signify that belonging to a network is a key contributing factor to adopting AI technology. This may be challenging for rural SMEs as, by nature, they do not exist within an industrial cluster and may not benefit from co-location advantages seen with urban SMEs.

In terms of future plans, rural AI adopters indicated higher levels of intentions to export in the future and expressed a greater interest in research and development. Hence, the AI adopters are not only doing more now but are planning more in the future.

1. INTRODUCTION

In 2023 a McKinsey report announced that: *AI has permeated our lives* (Chui et al 2023). This carefully worded statement highlights that AI has come into our lives in many ways, via smartphones, internet searches as well as Apps such as Google Bard, now known as Gemini. What has essentially made AI so different is the way it has been adopted and 'permeated' into business and home lives as unlike many prior technologies it is exceptionally easy to use. Ease of use has long been a determinate of technology adoption (Adams *et al.*, 1992; Davis, 1989). This is the case for consumers, and organisations with SMEs facing particular challenges and decisions. While benefits of technologies such as cloud computing are well known, barriers to adoption, in particular ease of use, lead to limited uptake within SMEs (Wei and Pardo, 2022).

The more rural, and remote an SME's location is, the greater the challenges SMEs face (Laurin *et al.*, 2020). SMEs in rural areas face particular challenges, and a 'digital divide' between urban SMEs with respect to capacity, such as broadband access and internal firm-based factors (Bowen and Morris, 2019). This makes the adoption of AI, while seemingly low in terms of obstacles generally an enhanced issue for rural located SMEs. The British Chamber of Commerce reported that only 56% of rural SMEs indicated they had reliable internet connectivity, far lower than urban located operations (2023). It is known that the level of digitisation influences uptake (Bettoni *et al.*, 2021), which exacerbates the issue.

There is a wealth of evidence which indicates that there can be benefits derived from AI adoption by SMEs (Mikalef *et al.*, 2023). As such, based on this pejorative view, there have been studies to identify the barriers to adoption of AI technologies (Baabdullah *et al.*, 2021). However, in the B2B literature there has been a long tradition of network research, relationships and innovative practice (Pittaway *et al.*, 2004). There is growing evidence that networks are important to the adoption of AI, yet questions remain about what AI enabling partnerships might look like (Petruzzelli., et al 2023). Network members, power dynamics and technical competencies have been identified as areas of interest (Keegan *et al.*, 2022). This research, as stated, is focused on adoption, and remains in a neo-developed state. Beyond this – what makes SMEs persist with AI has extremely limited findings to date.

The research draws upon recent artificial intelligence (AI), small medium enterprises (SMEs) research (e.g. Baabdullah et al., 2021; Sharma et al., 2024) and marketing business-to-business network literature (e.g. Chen et al., 2021; Keegan et al., 2022;

Mariani & Okumus, 2022), contextualised within the regional/rural setting. We aim to further develop models of AI adoption and usage, specifically within SMEs (Bowen and Morris, 2019, 2023; Issa *et al.*, 2022) and then enhance insights of the persistence of AI usage in SMEs.

The report hereafter is presented in the following structure. In section two we present literature related to AI, SMEs and rural SMEs, in particular discussing the adoption and use of new technologies. In section three we present a brief methodology followed by our results. This is in turn followed by our key findings which are discussed in section four. We then conclude in section five, where we also identify a number of public policy issues which arise from our research.

2. RELEVANT LITERATURE AND PAST RESEARCH

The relevant literature falls into several streams, we first discuss what AI is and the controversy around the adoption of AI. Then we move to the context of rural SMEs, followed by AI and technology adoption more broadly. Rural businesses have been argued to be a potential beneficiary of AI, but prior to engagement in these areas. It leads us to discuss a question posed '*what if the end adopters do not benefit as much as the bulls think they might*?' (Parikh, 2024), and the capacity of AI may have been overplayed (Simon *et al.*, 2024).

2.1 Artificial Intelligence Defined

AI is not entirely a new concept: IBM notes that AI, human intelligence exhibited by machines was derived in the 1950s, with machine learning arriving in the 1980s where AI learns from historical data. This was followed in the 2010 by deep learning, where models that mimic human brain function were developed (IBM, 2024). The term AI was coined in 1955 by John McCarthy, and through the 1950s and 1960s gained attention for the possible outcomes it may achieve (Brynjolfsson and McAfee, 2017). In 2020 one article stated that AI was once thought of as a computer science project had now taken centre stage, both in terms of academic discussion and practice (Ågerfalk, 2020). AI is sexy, AI is cool – amongst other things (Heaven, 2024).

In 2024 an article in the economist discussed the definition of AI and concluded it was something that a court may decide (Economist, 2024), AI is notoriously difficult to pin down via an academic, practitioner and policy lens, all of which differs (Krafft *et al.*, 2020). IBM define AI as '*Artificial intelligence (AI) is technology that enables computers and machines to simulate human learning, comprehension, problem solving, decision making, creativity* *and autonomy*.' (IBM, 2024). The original definition was developed by Christopher Manning in 1955: '*the science and engineering of making intelligent machines*'. Using the lens of an SME, AI must be considered quite broadly, as there are many functions of AI. When referring to AI, one broader conceptualisation is that AI is a discipline that simulates human skills which include abilities of reasoning, learning, and problem-solving (Jafarzadeh *et al.*, 2024).

AI can be defined in terms of what it can do, and the abilities of AI have been overset as a timeline by McKinsey, from machine learning, through deep learning to generative AI (Blumberg *et al.*, 2024). In a survey of managers who are not exclusively SME by nature; manufacturing and risk management were the first uses of AI, followed by sales/marketing, product/service development, strategy and cooperate finance (Blumberg *et al.*, 2024). Within the SME literature, decision making, CRM, process development, transport management, staff management, innovation, value development are amongst the many functions we find in the SME literature. It is perhaps this, what AI can do that defines it for SMEs.

2.2 Artificial Intelligence Controversy

Despite the emergence and general acceptance, questions about AI perplex and leave an 'opaque picture'. AI is often sold as something that would offer a myriad of improvements to our lives and work, yet there is a dark side of AI (Mikalef *et al.*, 2023). There are great challenges and harm which can be done via AI (Wirtz *et al.*, 2020). The negative impacts spread to consumers, business and to society (Belanche *et al.*, 2024). Therefore, albeit good can come from AI, care must be given to limit negative consequences of AI adoption (Rana *et al.*, 2022). Staff expectations, the inability of AI to be accountable, and errors are some of the reasons that have been associated with AI's dark side within the organisation (Papagiannidis *et al.*, 2023). Poor service design and consumer interactions by AI show the link of potential dark side outcomes of AI stretching beyond the organisation (Belanche *et al.*, 2024). Consumers, may also have issues with surveillance, another dark aspect of AI and concerningly the surveillance and privacy impacts may have more impact on women than men (Hu and Min, 2023). Negative impacts on customers/consumers can have many dimensions which can happen across many sectors (Barari *et al.*, 2024). For SMEs the quality of the data can also lead to adverse outcomes through poor recommendations provided by AI (Dwivedi and Wang, 2022).

Beyond the business issues, there are also the location factors to consider in particular the rural dimensions of SMEs may exacerbate some of the above. AI as a technology needs to be analysed with both a responsible and a rural lens, exploring what it means in a rural location rather than assume broader impacts simply apply (Cowie *et al.*, 2020). Rural SMEs form the backbone of some smaller communities, not only providing employment, but also sponsoring sports teams, donating to rural facilities and contributing to the rural economy and society. Thus, any downsizing is likely to have a profound effect on the employees, however the SME may still be in a position to provide the money for community sponsorship and activities. As such AI is a complex issue in rural regions, which also face the technological challenges, access to training and other innovation adoption issues.

2.3 Rural Small Medium Enterprises

In general, SMEs cannot be ignored by researchers and policy makers as they create employment opportunities, contribute to economic growth and enhance social stability; however, they face challenges when adopting AI (Sharma *et al.*, 2024).

2.4 Drivers of AI and Technology Adoption

The wealth of evidence indicates that there can be benefits derived from AI adoption by SMEs (Mikalef *et al.*, 2023). As such, and based on this pejorative view, there have been studies to identify the barriers to the adoption of AI technologies (Baabdullah *et al.*, 2021). Here we further aim to explore adoption of technology. Where AI is not new, and is relatively compatible with most SMEs, the challenge is to identify frameworks which can best explain why some do and why some choose not to implement AI.

In 2023, the Accenture Chief Executive Julie Sweet stated in the FT that most companies were not ready to deploy AI, lacking infrastructure to ensure safe deployment (Foley, 2023). Goldman Sachs in an 'educational report' also indicated that spending on AI infrastructure was needed, and as such the providers of AI infrastructure could see rises in share values as demands from organisations eventuate (Goldman Sachs, 2024). In general, it is hard for SMEs to adopt technology and innovate (Bettoni *et al.*, 2021), the special dimension in particular for rural SMEs is exacerbated by location (Bowen and Morris, 2023). We see issues facing AI adoption at both a firm level and a macroenvironmental level (HRM and Brexit for example). To address this, we begin to look at the factors which have been found to drive innovation adoption in prior research beginning with networks, then we move to a well-known model which has limitations (namely lacks network elements).

2.4.1 Networks

In the B2B literature there has been a long tradition of network research, relationships and innovative practice (Pittaway et al., 2004). There is growing evidence that networks are important to the adoption of AI, yet questions remain about what AI enabling partnerships might look like (Petruzzelli., et al 2023). Network members, the power dynamics and technical competencies have been identified as areas of interest with regards to technology adoption (Keegan et al., 2022). Where networks are a critical part of technology adoption (Beckmann *et al.*, 2023).

Networks are a place to learn, understand and to help adopt technologies. They create momentum, for example if a supplier uses a system then there becomes a push to adopt that system. No single firm can keep pace with all technological development, thus the network – both informal and formal becomes an integral part of technological adoption (Pyka, 1997). Thus, engagement in networks, either formal or formal could lead to increased adoption of AI.

There are a number of risks that come with supply chains, one key issue being the management of data across and between the actors in the supply chain (Foroohar, 2024), where networks and relationships are by nature inherent with risk (Huang *et al.*, 2022). Indeed, during the Covid pandemic personal networks and professional networks shrank, and this reduction in network size can lead to a downturn in creativity (King and Kovács, 2021). Networks are a space where resources can be shared and developed where risks can also be shared. This makes networks a central part of the adoption and use of AI.

2.4.2 Beyond SME (firm) Factors: Covid-19, Sustainability and Brexit

SMEs in rural areas face a variety of challenges, many of which impact upon their ability and even desire to adopt new technologies. In 2024 the Consultancy group McKinsey predicted that more organisations would sample AI and eventually we would begin to see more returns from AI, leading to a job spike in coming years (see https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-top-trends-in-tech). However, this needs to be commensurate with broader trends, while AI may be the focus of much academic and practitioner insight, numerous multifaceted challenges exist. The interaction of Covid-19, sustainability and Brexit has had a profound effect on non-urban SMEs in many ways, and in particular in the hospitality sector for example (Dowell *et al.*, 2023). In short, the broader environment cannot be ignored when looking at the adoption of new technologies such as AI.

Covid-19 had an immense effect on SMEs, in particular the pandemic ate away at savings, and indeed some SMEs did not have enough savings to work through the pandemic (Brown and Cowling, 2021). Studies that investigated Covid-19 in the UK indicated that there was a special element, where SMEs in some regions were more resilient than others (Brown and Cowling, 2021). This suggests that rural SMEs would be adversely negatively affected at the time, and this would lead to scarring effects within the SMEs in these areas. This has also spread to innovation, with SMEs cutting innovation spending to sure up finances (Trunschke *et al.*, 2024).

Sustainability has been an area of much interest to academics and policy makers. Arguably small firms and start-ups will use technology to create social value, that being ae benefit to society as well as creating an economic value (Vrontis *et al.*, 2022). Further, adoption of AI may be a part of meeting sustainable development goals (Žigienė *et al.*, 2019). Thus, SMEs with a sustainability drive may be more likely to adopt AI. However, there is little evidence that this will be the case in rural areas, as despite their best intentions, location issues may prohibit the sustainable drive.

Part of the economic tapestry in the UK is the departure from the European Union (EU) termed Brexit. Brexit was argued to have a special dimension, and SMEs intended on lowering levels of innovation before the full exit (Brown *et al.*, 2019). The uncertainty affected trade in a negative way, and the risk/uncertainty also had a regional dimension (Thissen *et al.*, 2020). Organisations (SMEs in particular) needed to be dynamic in their response to Brexit, to be adaptive and change oriented (Duarte Alonso *et al.*, 2019). In the adoption of new technology, even aspects such as EU consumer protection and data protection become serious considerations. Thus, Brexit will arguably influence the rural SME, they may adopt to survive or hide from it to save money. AI requires seamless human and technological interactions, basically the technology relies on good people (Dwivedi and Wang, 2022), Brexit has been associated with human resource related issues.

2.4.3 A Model to Explain Technology Adoption in Rural SMEs

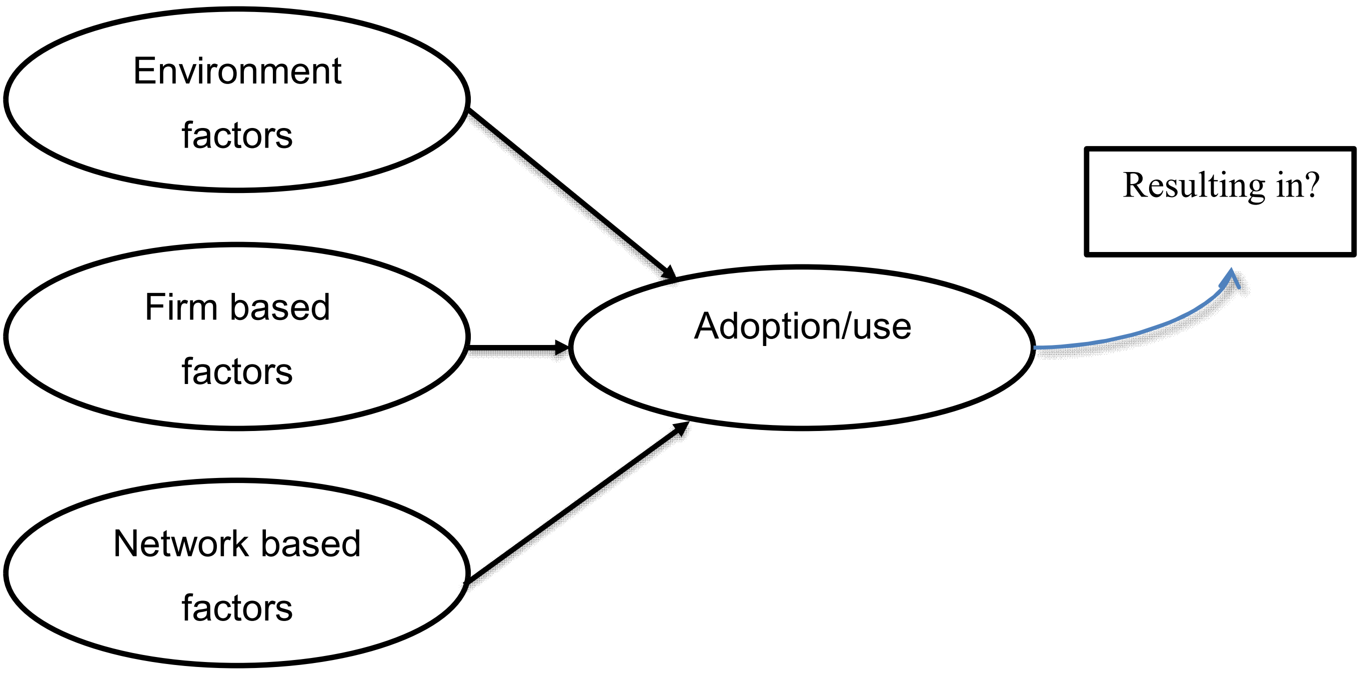
There are two main models which may help to explain the uptake of new technologies, the adoption of innovation. Both models offer insight, but are not complete and do not speak to a new technology such as AI where most SMEs have the tools like software, and also the human resource capacity as AI is a relatively easy technology to adopt.

The Technology-Organization Environment framework was initially developed within the field of information systems and therefore seems appropriate for consideration for application into AI adoption. Since it has been broadly applied and extended to many sectors. The key principles of the framework are the influence of characteristics of the technology, the organisation context and the external environment (Tornatzky and Fleischer, 1990). A key debate of TOEs is the research around size of the organisation, with larger firms more likely to adopt innovations, the debate has called for more inclusive measurement of the organisation (Baker, 2012). The presence and acceptance in general that different size (and structures) of organisations take on technology in different ways makes the framework suitable for SME analysis. In this research, SMEs are by nature small, and starved of resources in many cases. But the model may offer some insights.

The main principles of the Technology Acceptance Model (TAM) proposed by Davis, (1989) are focussed on the technology itself and its useability. The key factors being Perceived Usefulness (PU) of the technology and Perceived Ease of Use (PEU). Combined these two factors determine the technologies adoption and acceptance (Marangunić and Granić, 2015). A review of TAM findings has identified inconsistencies in predictive results (Legris *et al.*, 2003). While often criticised the model does help to explain innovation adoption and has been used in SMEs in prior research.

Using a predetermined model approach to assess innovation adoption, in particular something like AI would require a survey approach, and the approach is arguably not well suited to secondary data which does not measure attitudes. What is most notable is that neither model includes networks. Access to networks, and more importantly seeking information for networks is a strong predictor for technology adoption. These models are also not ideal for rural SMEs as measuring human resource capacity, even the need for a new technology is difficult.

2.4.4 Model for SMEs in Rural Areas



3. METHODOLOGY AND RESULTS

The research used data collected as part of the Longitudinal Small Business Survey (LSBS). The (LSBS) has been running since 2015, and is a UK wide longitudinal survey, with 2022 the most recent wave and this data the focus for much of this research. The sample includes businesses of less than 250 employees, with owners and managers responding from a stratified sample drawn from Scotland, Wales, Northen Ireland and England. The LSBS focuses on SMEs; investigating business dynamics, finance, innovation and areas such as AI. The sample is focussed on small business, selected from a variety of sectors which allows for insightful investigation. The sample is large and meaningful, yet the number of AI adopters in rural areas is relatively small.

We use several methods to analyse the adoption of AI in rural areas. ANOVA, the analysis of variance, Chi-square tests and probit regression were all utilised. ANOVA is a statistical technique used to determine if samples from two or more groups come from a population with equal means (Hair *et al.*, 2018). This allows us to test rural adopters and rural non adopters as groups. We hen examine variables such as income, turnover and other metric variables. Alternatively, when the variables are nonmetric, we use a contingency table. This is a cross tabulation of the categorical variables where the responses are reported as frequencies and percentages that fall into each cell of the matrix (Hair *et al.*, 2018). The significance of this can be examined with Chi-square. The categories of rural adopters and non-adopters are then used to see if categorical and binary variables such as expert yes/no are different amongst the categories. Finaly, we use binary regression, which is appropriate when the dependent variable has two alternatives only (Hoetker, 2007). The probit is a form of regression when the dependent variable has only two values 0/1. Which allows us to understand the probability that the dependent variable takes on the value zero or one is conditional on a set of explanatory variables (Horowitz, 1982). Thus, we are able to use a set of explanatory variables to understand the adoption, and in essence the non-adoption of AI.

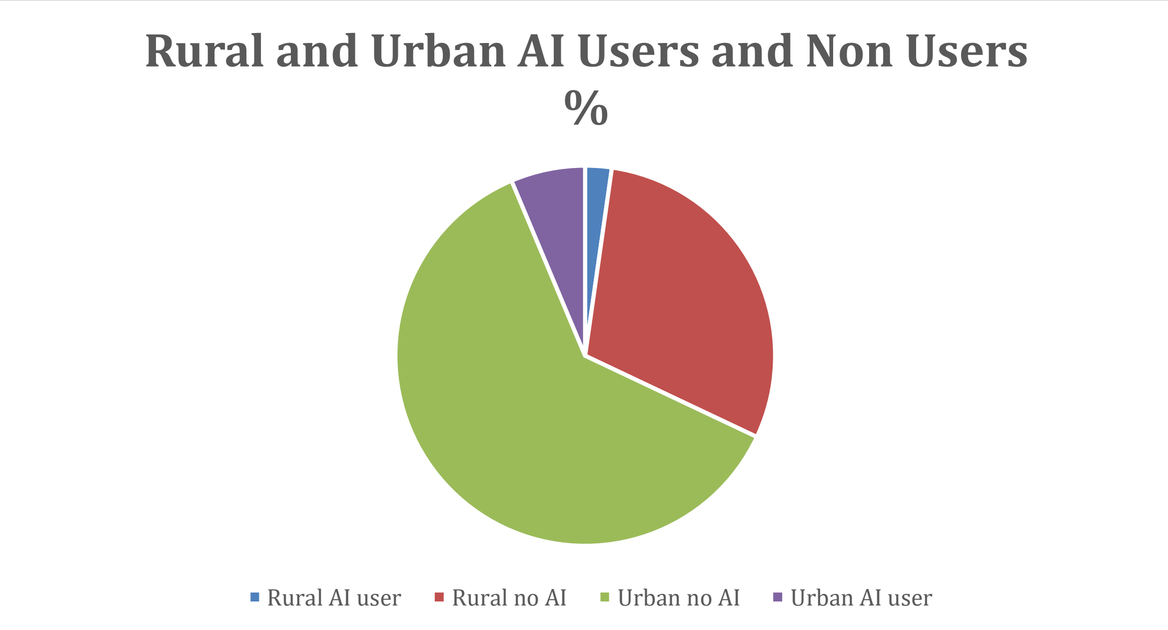
3.1 Descriptive Analysis of AI in Rural SMEs

The LSBS measure adoption of AI, and this has in the most recent survey change in the questioning around AI. The design of the LSBS means that not all participants answer the same questionnaire items during each round. In general, most descriptive statistics about SMEs are available in each round and answered by all respondents. The LSBS is designed to be representative of the UK Nations and based on the overall sample where 77.43% were drawn from England, 9.51% Scotland, 6.95% Wales, 6.10% from Northen Ireland.

For the rural SMEs 70.46% were from England, 10.20% from both Scotland and Wales and the remaining 9.14% from Northen Ireland. There is no significant association between the Nation and rural SME AI use ($p>0.001$).

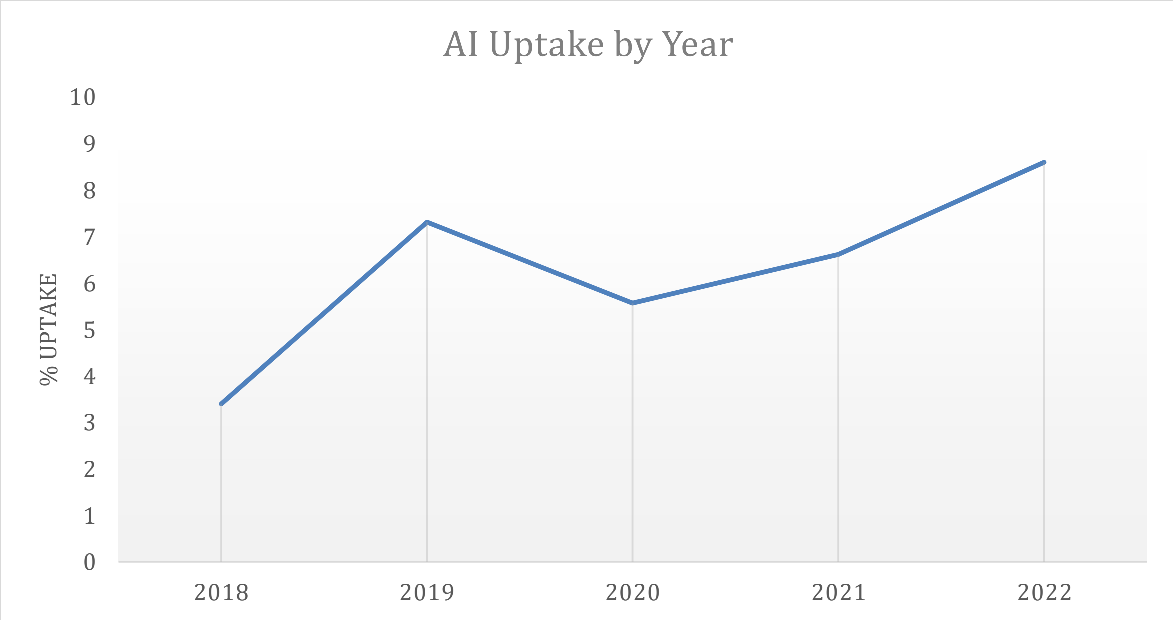
Broadly, for the year 2022 there were n=9492 SMEs in the sample, of which n=3040 (7.10%) were classified as rural SMEs. Of the rural SMEs n=213 (7.01%) were 'using' AI, which was significantly lower than the urban part of the sample. This was significantly different to the urban subsample (n=6452), with n=603 (9.35% of the urban subsample) having adopted AI. For urban SMEs the level of AI uptake was proportionally higher than the rural SMEs, and significant ($p<0.01$).

Diagram 3.1 Rural and Urban Users all Sample Percentages



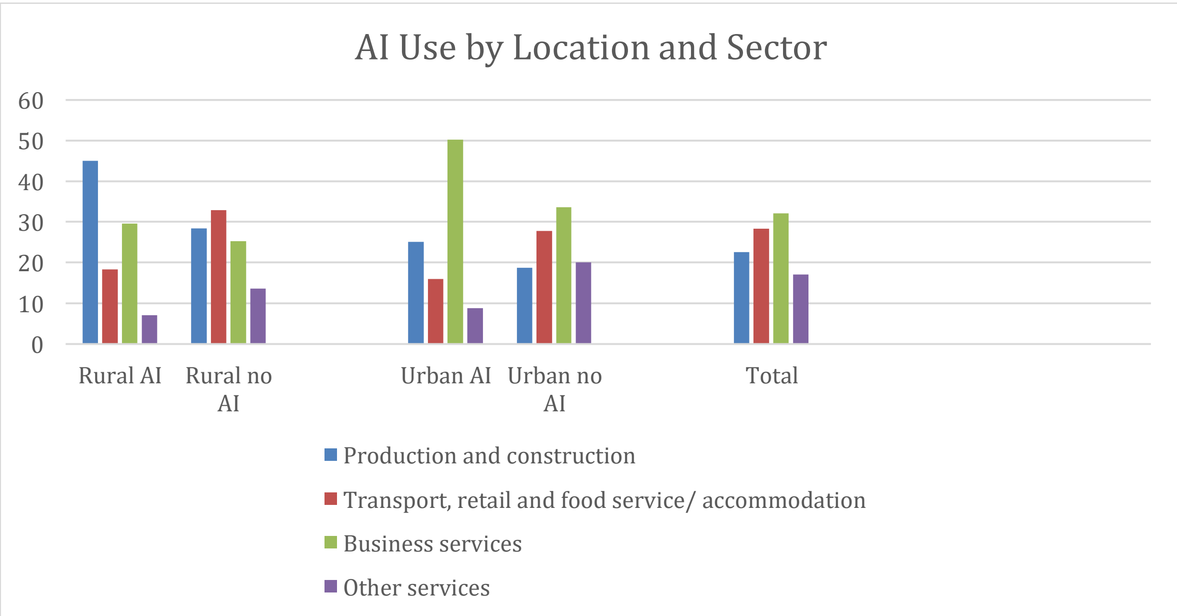
In terms of AI adoption, there has been steady growth in adoption since 2018, albeit a decline which coincides with the Covid-19 pandemic. For each year, different subsets were used, as such, not the same respondents were asked each year. However, the results a generalisable to the broader sample, and to SMEs in general. In 2018, 3.40% (n=126 of 3706) had taken on AI, in 2019, some 7.31% (n=131 of 1791) and then in 2020, the percentage decreases to 5.57% (n=78 of 1400) and then increases in 2021, to 6.62% (n=124 of 1873) and in 2022, to its highest level of 8.60% (n=819 of 9524). Thus, as seen in Diagram 3.2, there is a general increase in the uptake of AI over the past five years.

Diagram 3.2 Percentage of AI uptake by Year Whole Sample



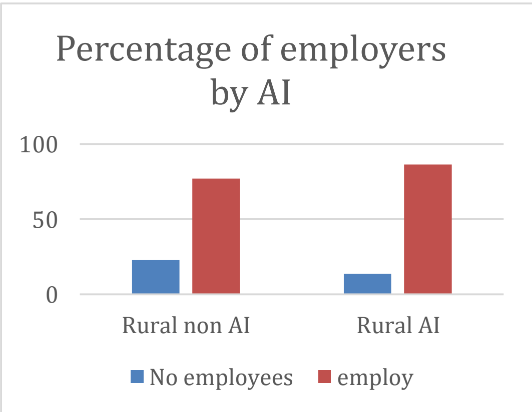
Of these rural AI users, the sector breakdown was: 45.07% in production and construction, 18.31% in transport, retail, food and accommodation services, 29.58% business services, 7.04% in other services. There is a significant difference across the sector of rural users of AI ($p<0.001$) which is a pattern also seen in urban locations. For rural SMEs the transport, retail, food and accommodation services could gain from adoption where smart menus, smart logistics are areas that invite growth.

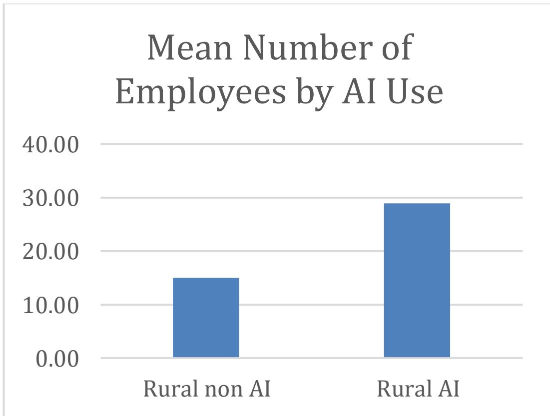
Table 3.1 AI Users by Location and Sector



The LSBS also includes turnover, where each wave of the survey SME respondents asked about their turnover, to estimate it and be relative to prior years, and finally to project what it may be in the forthcoming year. From the data the turnover for the rural AI users was £6,215712.30, well above the rural non-users (£2,265763.40). The difference in stated turnover is statistically significant ($p<0.001$) and reflected in urban comparisons. Of the Rural SMEs 86.38% had an employee, and this is significantly ($p<0.01$) more than the non-AI rural SMEs, 77.08%. The number of employees was also far higher, with mean=28.91 and mean =15.02 for the AI and non-AI rural SMEs respectively.

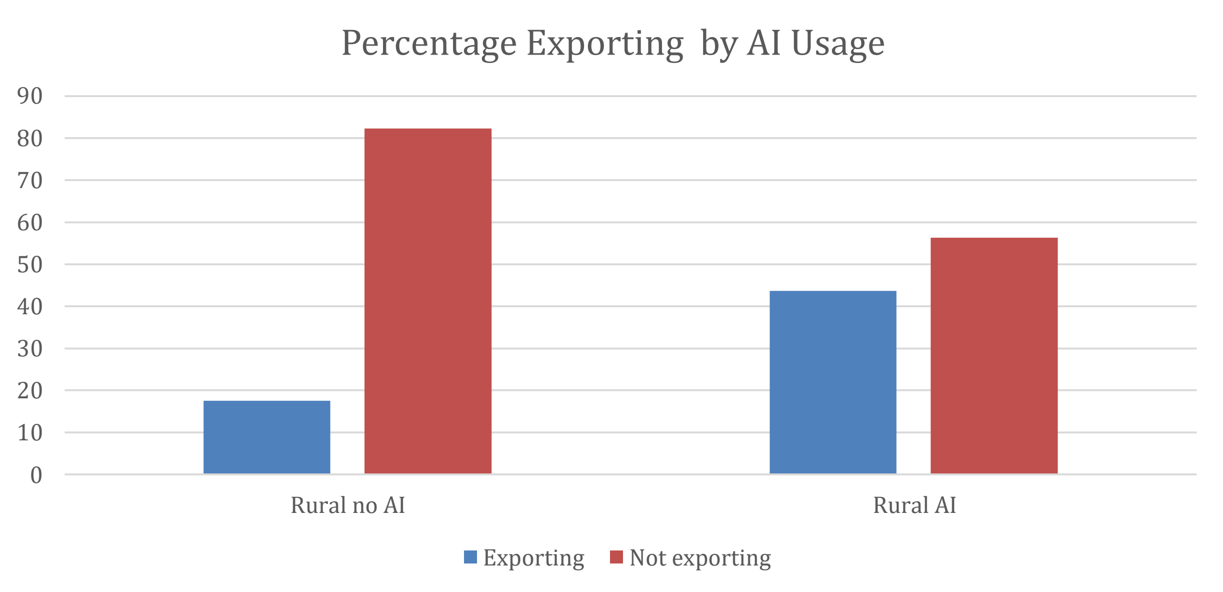
Table 3.2 Employee by AI Users and non-Users





The ownership structure of AI versus non-AI does not bring forward any statistical differences. Between AI users and non-users there are no differences in family ownership, ethnic ownership ($p>0.01$). Yet the AI users have a higher level of all male ownership/directors 46.01% versus 40.54% and lower levels of equally led (18.31% v 23.77%) and women only (13.15% v 19.28%). In terms of business profile, for the rural SMES n=587 (19.31%) were exporting goods and/or services. In terms of breakdown, rural SMEs using AI n=93 (43.66%) were exporting as opposed to n= 494 (17.47%).

Table 3.3 Percentage of Exporting Rural SMEs by AI Use



3.2 AI User Intentions

Having briefly outlined the SME characteristics, we now move to examine the intentions of AI adopters. This speaks to the question of AI – good or bad for not only rural business, but also will the productivity increases lead to a reduction in staff. This is a fundamental question that underpins AI research and whether it is dark?

In terms of expected turnover in the coming financial year, 48.36% of the rural AI users were expecting and increased turnover, as opposed to the non-AI rural cohort, here only 33.96% expected an increase. In the same order, 38.50% and 49.52% expected turnover to remain the same as the previous year. Thus, we see a far more positive outlook from the AI users than the non-AI group.

For SME future planning not all respondents answered the relevant questions owing to the survey design. Thus, only 51 users of AI in rural areas are included for this brief section analysis. For future plans beyond this[1] 76.47% of rural AI users wish to enhance their staff through skills development, more than the rural non-users, 58.69%. Furthermore, 80.39% of rural AI users wished to increase their staff size within the UK, compared with 55.70% of non AI rural. In terms of innovation, 66.67% planned to launch new offerings, 64.71% planned to invest in research and development, and in both cases, this was higher than

[1] The LSBS sample includes internal cohorts, and for some parts of the questionnaire only one cohort will answer the questions. For future SME plans n=2399, rural n=753, rural AI users n=51

the rural non-AI users. In terms of exporting, 39.22% of rural AI adopters were looking for enhanced exporting output, above the non-AI users, 13.68%.

Thus, despite the smaller numbers in the analysis we identify a clear trend. AI will not seemingly have any negative effects on the employees, nor the regains from which the SMEs are based. The AI adopters are looking to train staff, enhance exports, and innovate with new products in the coming year at levels far higher than the non-AI SMEs. If these plans materialise, AI can be seen as a positive factor based on this sub-set of our analysis.

3.3 Predicting AI Uptake in Rural SMEs

The analysis now moves to predictive, with the use of a binary probit model to understand the 'take up' or adoption of innovation, specifically AI. We analyse this using rural adopters of AI and non-adopters of AI as the dependent variable. We control for a number of factors, including SME size, age and location, however, to simplify reporting we do not discuss these. The probit regression is used when a dependent variable is 0 and 1, and we estimate the probability of change (Kissell, 2021). The probability of this change is based on explanatory variables which act as independent explanatory variables (Kissell, 2021). In this case, the rural non-adopter = 0 and the rural adopter of AI = 1, which is based on the 2022 data wave. We estimate four models, (1) environment factors, (2) SME internal factors, (3) network factors and a (4) combined regression. There was a barrage of post-hoc testing completed to ensure the validity of the results. Before we work through the probit analysis, we will briefly speak to the variables included.

The nature of the data collection process influences the ability to analyse the data. The full sample is broken into three sub-samples, these are referred to as cohorts A, B and C. As such variables need to be constructed for the analysis, or variables are selected form the most recent year of inclusion. This requires careful management of the data and the creation of indexes for some. This is done in accordance with Wooldridge's recommendations on pooling data (Wooldridge, 2010, 2013). This is not a panel regression as the participants have been asked only once about the dependent variable AI for the most. The dependent variable does not vary over time which is a requirement of panel regressions (Ward and Leigh, 1993). Therefore, we use a pooled set of explanatory variables to maximise the number of total observations. This creates an order for the explanatory variables.

The first regression contains Brexit, Covid, Sustainability and Environment. Brexit, the impact of Brexit on an SME was found to have a negative effect. While sustainability and environment were found to have positive effects. Covid has no significant effect.

The second regression contains strategic planning and financial seeking behaviour. Having a strategic plan was found to significantly and positively influence AI adoption. Financial stability was not found to influence AI adoption. Having an innovative past also had a significant effect on AI adoption.

The third regression contains networks, here seeking information from the network is measured. While social networks are of great importance it is only the professional networks, and specifically if a SME was seeking information. This was found to have a significant positive effect on AI adoption.

The final regression included the SME based, environment based and network factors. The results mirrored those of the prior regressions, with Brexit, sustainability green environment, business planning/strategy, innovative past behaviours and network engagement all having a significant effect on AI adoption.

4. CONCLUSIONS AND POLICY IMPLICATIONS

There are various implications and conclusions drawn from this work. These are discussed in order below. Rural technology adoption, and participation in the 4th industrial revolution is dependent on connectivity and broadband access (Cowie *et al.*, 2020). This is highlighted with what has been labelled the digital divide, where rural SMEs lack access and have less faith in providers (Bowen and Morris, 2019). The first contribution is that based on intentions for the coming period AI will not be a bad presence for the SMEs and their locations – the intentions are to grow not reduce. Based on this we have a number of key conclusions to highlight.

4.1 AI Can be Good

The initial findings here suggest that AI will not drive mass job cuts, productivity drives that decimate rural areas and thin SME structures. In fact, our research finds the opposite, where most SMEs in rural areas who have adopted AI are looking to expand, to grow and to export. This can mean positives for the SMEs and the rural locations they reside. Therefore, AI is not the tool of bad SMEs looking to reduce workforces.

4.2 Networks and AI

There have been studies which have indicated that the rural location, and lack of networking opportunities does not 'hold back' innovative process (North and Smallbone, 2000). In contrast, there is also a wealth of findings which suggest the importance of networks (Lewandowska *et al.*, 2016; Zeng *et al.*, 2010) even social networks have been found to influence innovation potential (Ioanid *et al.*, 2018). Yet in general it is conceded that special challenges faced by rural SMEs can be overcome using relationships, that is innovation adoption challenges can be managed via relational strategies (Beckmann *et al.*, 2023). It would appear from a broader analysis of past research that the location of an SME and rural location interact in a way that influences innovative outcomes.

Here we find networks, seeking information from formal networks as being essential. For rural SMEs this may be challenging owing to geography and digital connectiveness, however reaching out and engaging is essential.

4.3 The environment

Sustainability, both more broadly and green initiatives have been considered in this research. The proposition is that more sustainability driven SMEs will adopt AI to reduce the impact on their carbon footprint, and generally reduce their impact upon society (Chaudhuri *et al.*, 2022). Yet in common arguments and in the news, we see that the carbon footprint of AI is not so clear, with AI technologies consuming huge amounts of energy (BBC, 2024).

A sustainability drive and a green environment drive have a positive impact on AI adoption. If sustainability is part of the SMEs agenda, then it will lead to an enhance probability of AI adoption. AI can be included and retro fitted to sustainability policy to enhance AI uptake and sustainability outcomes.

Covid policy to enhance innovation and adoption of innovation has been a mismatch which shows patchy levels of success (Patrucco *et al.*, 2022). In particular, rural post covid policy has been disjointed, with effects from cancelling HS2 for example, and even transport policy such as non-peak travel times on Scottish Rail Network – these two and others have a negative effect on rural logistics, commuting and even location of operations decisions. This is parlayed by communications and technology slowdowns post covid and movements to reduce government spending (in Scotland). It appears that Covid has not shocked rural SMEs into adopting AI. This also parlays with the fact that rural SMEs who have adopted AI are looking to downsize, indeed if an SME had post Covid issues with regards to HRM we would see a positive effect on adoption, but we do not. This furthers arguments that AI is ok and not simply adopted to reduce staff levels.

4.4 Firm based Factors and AI

There is a large body of literature that looks at firm characteristics of SMEs and the adoption of innovations. We identified several factors, these being greater turnover, more likely to employ, and greater numbers of employees. We also found that the Rural SMEs who have adopted AI have higher levels of male owner/directorship. While these formed background variables in the causal analysis, they are important factors.

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APPENDIX

Table A1 AI Use by Sector and Location

	Production and construction	Transport, retail and food service/ accommodation	Business services	Other services	Total
Urban non AI	1,092	1,622	1,965	1,170	5,849
	18.67%	27.73%	33.6%	20%	100
Rural non AI	802	928	714	383	2,827
	28.37%	32.83%	25.26%	13.55%	100
Urban AI	151	96	303	53	603
	25.04%	15.92%	50.25%	8.79%	100
Rural AI	96	39	63	15	213
	45.07%	18.31%	29.58%	7.04%	100
Total	2,141	2,685	3,045	1,621	9,492
	22.56%	28.29%	32.08%	17.08%	100

Table A1 shows the allocation of urban and rural adopters and non adopters of AI by sector which they operate within.

Appendix A2 Variables Used

See below for the items used, and the response mechanisms. The items were all drawn from the LSBS survey. Response categories are in italics.

For Rural location: URBRUR1: detailed urban/rural classification, 31 classifications

URBRUR2: urban or rural derived from the 32 classifications

For AI: Which of the following, if any, do you use? Artificial Intelligence, Robotics or Automation: binary yes/no

Broad sector:

Label = ABCDEF - Production and construction

Label = GHI - Transport, retail and food service/ accommodation

Label = JKLMN - Business services

Label = PQRS - Other services

Can you please tell me the approximate turnover of your business in the past 12 months across all your UK sites? *State number*

Expectations of turnover growth in next 12 months.

Label = Increase

Label = Decrease

Label = Stay the same

Label = Don't know

Label = Refused

Including yourself, how many working owners and partners are there (in addition to the employees mentioned)? *State number*

Approximately how many employees are currently on your payroll in the UK, excluding owners and partners, across all sites? *State number*

Legal status?

Label = Sole proprietorship

Label = Private limited company, limited by shares (LTD.)

Label = Public Ltd Company (PLC)

Label = Partnership

Label = Limited liability partnership

Label = Private company limited by guarantee

Label = Community Interest Company (CIC, limited by guarantee or shares)

Label = Friendly Society

Label = A Co-operative

Label = Industrial and Provident Society

Label = Private Unlimited Company

Label = Foreign Company

Label = A trust

Label = An unincorporated association

Label = Company - unspecified type

Label = Other

Label = Don't know

Label = Refused

Age of business - summary.

Label = 0 - 5 years

Label = 6 - 10 years

Label = 11 - 20 years

Label = More than 20 years

Label = Don't know

Is your business a family owned business, that is one which is majority owned by members of the same family? *Yes/no*

Proportion of owners/directors that are women

Label = Women led

Label = Equally led

Label = Women in minority

Label = Entirely male led

Label = Don't know

How many employees did the business have on the payroll 12 months ago across all UK sites (still excluding owners and partners)?

Label = More than currently

Label = The same

Label = Fewer

Label = Don't know

Whether export goods or services. *Yes/no*

Whether social and environmental goals are main concern (sustainability)

Label = Your business's only concern

Label = Your business's primary concern

Label = Equal to financial or other goals

Label = Secondary to financial or other goals, or

Label = Non-existent

Label = Don't know

Label = Refused

Do you have a formal written business plan? (strategic planning)

Label = Yes - kept up to date

Label = Yes - but not kept up to date

Label = No

Label = Don't know

Label = Refused

Has your business introduced any new or significantly improved processes for producing or supplying goods or services in the last three years? *Yes/no*

New or significantly improved services in the last 3 years? *Yes/no*

New or significantly improved goods in the last 3 years? *Yes/no*

R2. How likely is it that you will approach external finance providers in the next three years?

Label = Very likely

Label = Fairly likely

Label = Not very likely

Label = Not at all likely

Label = Don't know

Networks: Whether used information or advice in the last 12 months - UK. *Yes/no*

For Covid and Brexit we use a dummy variables, that is a variable developed from other measures within the survey. This was done because of the nature of the survey design and to ensure we could keep as many respondents in the analysis as possible. A pooling of variables was used for simplicity, explanation and reporting, which is also a sound approach to data analysis. Covid was taken from items asked in 2020 and 2021, a sum of items which measured covid impact were developed into one dummy variable. For example: Have any of these plans been affected by the Coronavirus COVID-19 pandemic? With one example response: *Develop and launch new products/services.* The Brexit measure was also taken from a series of items. Respondents were asked a series of questions beginning with: Whether plans over the next three years have been affected by Brexit: with an example response *Invest in R&D.* For simplicity a sum of years was used from 2017 through 2022. We also develop the variables as indexes and had the same results.

Appendix A3 Descriptive Summary of Explanatory Variables (Urban and Rural)

Variable	Mean	Std. dev.	Min	Max
Brexit	5.878	0.389	0	6
Covid	19.579	1.290	0	20
Sustainability	3.702	0.592	1	4
Environment	2.230	0.717	1	3
Strategic planning	0.310	0.462	0	1
Finance seeking	0.229	0.420	0	1
Process innovation	0.322	0.790	0	6
Good/service innovations	0.328	0.470	0	1
Network engagement	0.274	0.4456	0	1

Appendix A4 Probit Regression Results Rural SMEs only

	All variables			Environment			SME/firm			Networks		
	β	se	p	β	se	p	β	se	p	β	se	p
Brexit	-0.192	-0.080	*	-0.33	-0.074	***						
Covid	-0.002	0.025		-0.03	-0.025							
Sustainability	0.202	0.064	**	0.1	0.057	*						
Environment	0.109	0.057	*	0.201	0.051	***						
Business plan (strategy)	0.254	0.078	**				0.307	0.076	***			
Finance seeking	0.114	0.080					0.18	0.079	*			
Process innovation	0.236	0.038	***				0.231	0.036	***			
G/S innovation	0.475	0.075	**				0.526	0.073	***			
Network engagement	0.209	0.075	**							0.452	0.07	***
Observations	2938			3020			2966			3021		
AR-2	0.1149			0.0263			0.0984			0.248		
Pr>Chi2	0.000001			0.000001			0.000001			0.000001		

Dependent variable 0/1 Rural AI non adopters = 0, rural adopters of AI=1.
*=p<0.05, **p<0.01, ***p<0.001
A Wald test was conducted for each estimate with results showing sound fit.

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