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RESEARCH PAPER

Advanced technology adoption in UK SMEs: what is the effect of external knowledge sources and what are the productivity outcomes?

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1. Executive Summary

Advanced and emerging technologies (AET), including artificial intelligence (AI), robotics, automation, and virtual and augmented reality (VR/AR), have considerable potential to support firm innovation and productivity. Yet, adopting these technologies can be particularly challenging for small- and medium-sized enterprises (SMEs) due to greater resource constraints. External information and advice may therefore play an important role in helping SMEs understand, evaluate, and adopt these new technologies. This research paper examines the relationship between the use of external information/advice and AET adoption among a sample of UK SMEs. In particular, this report investigates whether firms using external information/advice are more likely to adopt AET, whether the motivations for using such advice and its sources matter for adoption, and whether AET adoption is associated with higher levels of labour productivity. The analysis draws on the UK Longitudinal Small Business Survey (LSBS) between 2018 and 2021 and an analytical sample of 8,732 firm-year observations, using regression analysis and propensity score matching.

The following findings emerge from this research. First, between 2018 and 2021, only a small share of UK SMEs adopted AET, roughly 6.8% of the sample. Second, firms using external information/advice had an approximately 2.8 percentage-point higher predicted probability of AET adoption than non-users after accounting for other firm-level characteristics. Third, this statically significant positive relationship remains in the propensity-score-matched sample, where firms using external information/advice had an approximately 3.9 percentage-point higher predicted probability of AET adoption than non-users. Fourth, among firms using external information/advice, AET adoption was particularly associated with using advice for innovation and efficiency/productivity purposes and with obtaining advice from professional services and business/education sources. In contrast, government support (chamber of commerce, GOV website and local council/authority) was not significantly associated with AET adoption. Finally, AET adoption was initially associated with higher labour productivity, but this significant association diminished after matching. External information/advice remained positively associated with labour productivity across all models.

Overall, the analysis highlights the potential importance of external information and advice in the adoption of AET among UK SMEs. Based on the findings, policy efforts to encourage technology diffusion may want to consider the wider external knowledge and advisory environment of SMEs. Strengthening their access to relevant professional, business and education-based sources of advice, and ensuring that support is sufficiently focused on firms' innovation and efficiency needs, may help firms navigate the uncertainties associated with AET. Simultaneously, the productivity findings caution against the assumption that AET adoption alone necessarily translates into productivity gains, but further empirical research on more recent data is required in this regard.

Key Findings at a Glance

- Finding one: Between 2018 and 2021, only a small share of UK SMEs adopted AET, roughly 6.8% of the sample.
- Finding two: Firms using external information/advice had an approximately 2.8 percentage-point higher predicted probability of AET adoption than non-users, after accounting for other firm-level characteristics.
- Finding three: Firms using external information/advice had an approximately 3.9 percentage-point higher predicted probability of AET adoption than non-users in the propensity-score-matched sample.
- Finding four: Among firms using external information/advice, AET adoption was particularly associated with using advice for innovation and efficiency purposes, and with obtaining advice from professional services and business/education sources.
- Finding five: AET adoption was initially associated with higher labour productivity, but this association was no longer statistically significant after matching, while external information/advice remained positively associated with labour productivity.

2. Introduction

2.1 Background and Context

The recent and ongoing diffusion of advanced and emerging technologies (AET), including artificial intelligence, have ignited policy debates amongst policy makers due to their wider socio-economic implications which are yet to be fully understood. Importantly, AET include not only AI, but also automation, robotics, and virtual/augmented reality (VR/AR), and adoption of these technologies has taken centre stage in policy debates due to their transformative implications for firm competitiveness, labour markets, and economic growth (e.g., OECD, 2025). While AET are mostly associated with large, multinational corporations, there has been increased focus on how these technologies are being used by smaller firms, including small- and medium-sized enterprise (SMEs). This is against the backdrop of rising global uncertainties due to geopolitical shifts, rising costs associated with doing business (such as shipping costs) and climate-related actions - all of which pose strains on these comparably vulnerable firms. Since the start of the decade, SMEs have been catching up with large firms in adopting digital technologies more broadly, including social media and cloud computing services, however, many SMEs continue to lack the skills needed to fully exploit the potential of digital technologies (OECD, 2023). AET are somewhat even more advanced in their capabilities and potential to transform business, but less is known about AET uptake in SMEs to date.

This warrants further investigation, especially in a UK context with the UK aiming to strategically position itself as a global AI powerhouse as part of its wider *National AI strategy*, published in 2021. Specifically, the UK Government's National AI Strategy identifies the diffusion of AI across the economy as a strategic priority and explicitly emphasises the need for SMEs, alongside start-ups and larger firms, to have access to the people, knowledge and infrastructure required to respond to AI-driven technological change (DCMS, 2021). As of 2024, SMEs account for over 99,2 % of the UK business population and they are mainly found in construction, professional, scientific and technical activities as well as wholesale and retail trade as the primary sectors (DBT, 2024). Thus, a key concern is to understand whether, and how, UK SMEs benefit from this wider AI strategy and are able to leverage the opportunities associated with AET uptake, such as productivity, growth and innovation. However, in a survey on the future of the economy, only about a third (35%) of SMEs reported they actively used AI technology and had further appetite to unlock its full potential (British Chambers of Commerce, 2025). This suggests that AET adoption is not as prevalent across the UK SME population, highlighting a clear need to understand the underlying drivers and constraints.

SMEs are a highly heterogenous group and it may be down to firm-specific factors that explain why some SMEs engage in AET adoption over others. In this regard, recent empirical work has highlighted, for instance, the role of the dual engagement in research and development (R&D) *and* exporting, showing that those SMEs which engaged in R&D and exporting simultaneously had a higher likelihood of AET adoption; notably, R&D engagement was the primary driver, with exporting contributing only modestly (see Velez-Ospina & Breslin, 2025). R&D engagement is an important 'internal' form of knowledge creation within firms, explaining its role as a driver for AET adoption in SMEs. Moreover, many firms – including SMEs – increasingly turn outwards to receive knowledge and advice from relevant external stakeholders. Indeed, SMEs have been found to employ an 'open innovation' logic, integrating into wider networks consisting of relevant external stakeholders, which overall may support their technology upskilling and uptake (see OECD, 2023). Yet, extant research has offered relatively little insights into the role of external knowledge sources on AET adoption. Conceptually, it is plausible to assume that access to external knowledge reduces perceived information and capability constraints, thereby increasing SME managers' confidence to adopt complex, high-fixed-cost technologies, including AET (see also Jibril & Roper, 2025), but more empirical research is required.

2.2 Research Questions

External information and advice, e.g., from consultants, professional networks, or government support agencies, may encourage AET uptake amongst SMEs by providing expertise, guidance, and insights on industry 'best practice'. Firms may access different sources of external knowledge and advice, including industry bodies and trade associations, research institutions such as universities as well as government support agencies. In fact, previous research has highlighted the nuances associated with different knowledge sources, with some being more useful to firms, including SMEs, than others (Chen, Vanhaverbeke, & Du, 2016; Du, Belderbos, Leten & Vanhaverbeke, 2025). Moreover, the underlying motives for seeking external knowledge and advice may differ; SME managers may seek external knowledge for different reasons and on different topics, such as innovation, legal issues and leadership development. Thus, a key focus in this study is not only to understand whether seeking external knowledge is associated with AET adoption in UK SMEs, but also to uncover to what extend this is influenced by (1) the type of external knowledge source (2) and the underlying motive. Finally, a key question also revolves around the outcomes of AET adoption: Understanding the drivers of AET adoption in UK SMEs alone may not produce policy-relevant insights, unless AET adoption brings clear benefits to firms. Hence, understanding the association between AET adoption and potential productivity implications remains of high interest.

Against the wider background and context previously outlined and in view of the aforementioned key considerations around the drivers of AET adoption in UK SMEs, this report is guided by three interrelated research questions, which together underpin this research:

- Research Question 1: Is the use of external knowledge associated with the adoption of advanced and emerging technologies (AET) among UK SMEs?
- Research Question 2: How do the sources and purposes of external knowledge use relate to AET adoption among UK SMEs?
- Research Question 3: Is AET adoption associated with productivity among UK SMEs?

In answering these questions, this research offers the following novelties and contributions: First, it extends recent empirical work, based on LSBS data, on the importance of SMEs' internal R&D activities for AET adoption to the role of external knowledge and advice (Velez-Ospona & Breslin, 2025). This is in line with a growing body of literature on firms' increased dependence on external partners for strategic and innovative purposes, including SMEs' integration into relevant networks for digital technology uptake (see Heaton & Min, 2025; OECD, 2023; Zhang et al., 2023). Second and related, we add nuance by studying how the type of external knowledge source and the topic of it affect the association between the general use of external knowledge sources and AET adoption in SMEs. In this respect, our study builds on, and extends, previous research which has revealed how different external partners (such as universities, other businesses, trade associations etc.) affect relevant firm outcomes (e.g., Chen et al., 2016; Du et al., 2025). Third, we offer insights into the potential productivity gains for SMEs arising from AET adoption, thereby extending the few existing empirical studies to date (e.g., see Czarnitzki et al., 2023; Lee et al., 2022).

2.3 Structure of the Research Paper

This report is structured as follows. In the following section, we offer a review of the literature, highlighting relevant theoretical concepts and frameworks underpinning this research; this is then followed by an overview of relevant empirical evidence and a brief summary of the prevailing research gaps. Next, in Section 4, we detail our methodological approach, based on LSBS data, explaining our core variables, statistical analyses and limitations. Section 5 discusses the main findings in relation to our three research questions and includes several robustness checks. The report ends with conclusions and recommendations in Section 6. References and appendices are provided at the end of this report.

3. Literature Review

This section reviews the existing evidence relevant to the research questions set out in Section 2, starting with relevant theoretical concepts and frameworks underpinning this research, followed by a critical review of the empirical literature.

3.1 Theoretical Framework

The behavioural theory of the firm (Cyert & March,1963; Gavetti et al., 2012) underpins this research with its focus on 'bounded rationality', uncertainty avoidance and organizational learning. Through a behavioural lens, firms are seen to operate under bounded rationality, meaning that managers cannot possess or process all the information needed to perfectly predict the consequences of their decisions. One response is uncertainty avoidance. According to Gavetti et al. (2012: 6), "uncertainty avoidance is the tendency to choose decision rules that emphasize short-run responses to feedback, and hence require little forecasting, along with attempts to create a negotiated environment through coordination with interdependent actors." The notion of uncertainty avoidance is particularly relevant in the context of AET adoption: Decisions to adopt AET are inherently characterised by uncertainty, as firms may have incomplete information about their potential benefits, implementation requirements and implications for future performance, thereby having to rely on predictions. Such uncertainty matters especially for SMEs, which often are constrained in their available resources and specialised expertise through which emerging technologies can be evaluated. Thus, from a behavioural perspective, the use of external information and advice may provide one mechanism through which firms can manage this uncertainty. By drawing on the knowledge and experience of relevant external stakeholders, firms may obtain information that allows them to better assess the opportunities, requirements and potential consequences associated with AET adoption. Rather than simply discouraging firms from adopting unfamiliar technologies, uncertainty may actually create a need for external knowledge that enables SMEs to make such adoption decisions under conditions of bounded rationality and limited resources.

A second core concept of the behavioural theory of the firm that is particularly relevant to this research is organizational learning. While firms can learn directly from their own experiences (also known as 'learning by doing'), learning may also occur vicariously through the experiences and knowledge of external actors (known as 'vicarious learning') (see Huber, 1991; Levitt & March, 1988). This is particularly relevant in the context of AET adoption, where firms – and especially SMEs – may have limited prior experience on which to draw when evaluating potential AET. Hence, rather than generating all relevant knowledge internally through their own experimentations (likely incurring investments), firms can draw on knowledge from outside their organizational boundaries. External information and advice may therefore expose SMEs to the experiences, expertise and knowledge of other relevant actors, enabling them to learn about technological opportunities, implementation requirements and potential outcomes. In this regard, the use of external knowledge can facilitate vicarious learning and expand the knowledge available to firms when considering AET adoption. Moreover, because different external stakeholders and actors possess different knowledge and experiences, the potential value of such learning may vary depending on the source from which external knowledge is obtained.

Taken together, through a behavioural lens, it can be argued that uncertainty avoidance explains why SMEs may seek external knowledge and advice in the context of AET adoption, while vicarious learning explains how such externally accessed knowledge and advice may lead to desirable organizational outcomes.

While the behavioural theory of the firm provides important insights into how firms respond to uncertainty and learn from the experiences and knowledge of others, its primary focus remains on decision-making and learning within the focal firm. Given that this research is explicitly concerned with external knowledge and advice, a second important conceptual framework underpinning this research pertains to open innovation (Chesbrough, 2016).

The idea behind 'open innovation' is essentially that firms do not solely rely on internally generated knowledge (e.g., through in-house R&D) but purposefully draw on knowledge beyond their formal organisational boundaries to support innovation. In their influential paper on UK manufacturing firms, Laursen and Salter (2006) conceptualise this process in terms of firms' external search strategies, highlighting the importance of searching across external sources for knowledge that can *complement* firms' internal knowledge bases. Such external search is likely to expose firms to new ideas, expertise and information that would otherwise be difficult to generate internally. Hence, this perspective is particularly relevant for SMEs, whose more limited internal resources may constrain their ability to independently develop the knowledge required to evaluate and implement emerging technologies (e.g., see Lee, Park, Yoon & Park, 2010).

Specifically, applied to AET adoption, external information and advice may be an important mechanism through which firms – including SMEs – may access knowledge beyond their organisational boundaries. By complementing their internal knowledge base (e.g., generated through R&D), accessing external knowledge from relevant sources may enhance SMEs' ability to better evaluate and understand relatively unfamiliar technologies such as AET; this may then ultimately help with their adoption. Notably, Laursen and Salter (2006) empirically demonstrate, however, that the potential benefits of external knowledge search are not unlimited, suggesting an inverted U-shaped relationship between breadth and depth of external search and innovation performance. Thus, whether and to what extent accessing external knowledge, including information and advice, facilitates the adoption of AET in SMEs may be nuanced and not straightforward.

3.2 Empirical Evidence

Extant empirical research has investigated some of the relevant drivers for SME adoption of AET. Specifically, in the context of UK SMEs, Velez-Ospina & Breslin (2025) studied the role of the dual engagement in R&D *and* exporting, empirically showing that those SMEs which engaged in R&D and exporting simultaneously had a higher likelihood of AET adoption. Their empirical findings further show that R&D engagement was the primary driver, with exporting contributing only modestly. Hence, there is extant empirical evidence which suggests the importance of firms' internal knowledge base, generated through R&D. In terms of the role of external knowledge, including information and advice, there is also some relevant research, albeit outside the UK context. Specifically, in a policy experiment conducted in Nigeria, firms which engaged with external advisers were more likely to adopt certain digital tools compared to those which were offered training or consultancy services instead (Anderson & McKenzie, 2022). Nevertheless, more empirical research in the context of UK SMEs is required which considers how, and to what extent, accessing external knowledge may facilitate the adoption of AET.

Moreover, as noted by Roper (2023), slow diffusion of emerging technologies and knowledge among firms, particularly smaller and less productive ones, contributes to the UK's lagging productivity performance and widening within-sector disparities. Yet, to date, there have been relatively few empirical studies on how AET adoption affects productivity at the firm-level, despite the policy-relevant implications which could be drawn from such insights; e.g., in relation to education and employee training aimed at developing AET-specific skill sets. In the context of German firms, Czarnitzki and colleagues (2023) found that AI adoption was associated with higher firm-level productivity. This empirical finding held across different measures of AI usage, including an indicator variable of AI adoption as well as the intensity with which firms used AI methods for business processes. Moreover, in a Korean context and focused on firm revenue rather than productivity, Lee et al. (2022) found that low levels of AI adoption were not associated with significant revenue growth; rather, revenue growth emerged only as the intensity of AI adoption increased and firms made sufficient AI investments. Based on Taiwanese firms, Yang et al. (2022) reported that AI was positively associated with productivity and employment.

Overall, there is a recent and emerging body of literature and empirical studies which link external knowledge, AET and productivity. However, more empirical insights into UK SMEs are needed (see also Jibril & Roper, 2025) to further fill in the gaps of the opportunities brought by such AET.

4. Methodology

4.1 Research Design

The research design of this report is based on secondary analysis of the Longitudinal Small Business Survey (LSBS) which has been annually conducted by the Department for Business and Trade (DBT) since 2015. The survey is the largest and most comprehensive survey of small- and medium-sized enterprises (SMEs) within the UK and offers extensive and systematic insights into firms' characteristics, including their innovation performance, growth ambitions, turnover and exporting. Notably, it also contains key variables relevant to this research paper.

The LSBS has been used in prior studies on similar and relevant issues to the present report, including AET adoption based on the dual engagement of innovation and exporting (Velez-Ospina & Breslin, 2025), external advice for SMEs (Brown et al., 2024) and productivity implications of technology adoption (Liñares-Zegarra & Wilson, 2025). LSBS data has been used across an array of research reports and academic journal articles, overall offering considerable insights into UK SMEs (e.g., see also Gkypali, Love, & Roper, 2021). The research design presented here therefore builds on these recent and relevant studies to shed light on the main research questions, as stated above.

In this study, we investigate the association between the use of external knowledge and the adoption of advanced and emerging technologies (AET). Specifically, our main independent variable is based on the K2ALL item in the LSBS questionnaire: "*Whether used information or advice in the last 12 months – UK*". We computed a dichotomous variable for our analysis (see more details in 4.3) to understand whether and to what extent external information or advice are associated with AET adoption, which in turn was computed based on items F11D "*Which of the following do you use?: Artificial Intelligence, Robotics or Automation*" and F11E "*Which of the following, if any, do you use? Virtual Reality and Augmented Reality*" (see also Velez-Ospina & Breslin, 2025). To add further nuance to our findings, we also explore the underlying sources and motivations of the sought external information or advice, as well as likely productivity associations. Overall, our research design – as further detailed below – uses relevant LSBS data to shed light on the guiding research questions of the present report.

4.2 Data Sources and Sample

As previously discussed, the data source of the present report is the LSBS for which data is available, at the time of writing, between 2015 and 2024. The full dataset comprises of 50,601 unique firms which is the starting point of our sampling strategy. AET adoption, along with some other questions pertaining to technology, are only asked to firms allocated to Cohort C, whereby firms can enter and exit Cohort C over time. Moreover, questions regarding AET adoption were introduced in 2018 and they are consistently available only between 2018 and 2021 which defines the period of our analysis; notably, item F11E does exist beyond 2021 but then asks about electronic invoicing rather than VR/AR. Thus, we restrict our observation period to 2018-2021 which is consistent with previous studies on AET adoption (see Velez-Ospina & Breslin, 2025). Within this period, we restrict the sample to Cohort C firm-year observations for which AET adoption can be observed, resulting in an initial analytical sample of 8,750 firm-year observations which equates to 7,575 unique firms.

Additionally, we excluded firms which reported zero employees as these are non-employer firms, which resulted in the exclusion of 18 firm-year observations, equating to 17 unique firms, which reduces our sample to 8,732 firm-year observations, i.e., 7,558 unique firms. Notably, we impose no further firm-size restrictions, acknowledging that SMEs can be defined in different ways. For instance, particularly in the European context, SMEs are commonly defined as enterprises employing fewer than 250 employees. However, as the LSBS includes firms above this threshold, including firms that may have grown beyond it over time, we retain these observations in our sample and main analysis, rather than imposing an additional size restriction. We do, however, run some robustness checks on a sub-sample of firms with less than 250 employees, as further explained

below, to tease out any specificities applying particularly to these firms which empirically does not seem to be the case.

Overall, our final sample comprises of 8,732 firm-year observations, i.e., 7,558 unique firms, which represents a sub-sample of the LSBS on which we run our analyses. Before detailing the analytical methods, including further analyses and limitations, we offer several insights into the nature and characteristics of our sample. In particular, **Table 1** details external information/advice and AET adoption over time. It illustrates that the use of external information and knowledge is relatively stable over the observation period, ranging between 31.28% and 33.39% of firm-year observations. In contrast, AET adoption varies more substantially over time: While only 4.54% of firms reported AET adoption in 2018, this increased to 8.93% in 2019 and remained comparatively higher in 2020 (7.33%) and 2021 (8.66%). Across the full observation period, 32.12% of firm-year observations reported the use of external information or knowledge, while only 6.76% reported AET adoption.

Table 1: AET and External information/advice over time

Survey year	External information/advice, n (%)	AET adoption, n (%)
2018	1,125 (31.28%)	168 (4.54%)
2019	577 (33.39%)	159 (8.93%)
2020	436 (31.85%)	102 (7.33%)
2021	599 (32.75%)	161 (8.66%)
Total	**2,737 (32.12%)**	590 (6.76%)

Notes: Percentages are calculated based on non-missing observations for each variable. External knowledge is observed for 8,522 of the 8,732 firm-year observations. Firms count as AET adopters, if they used either (1) Artificial Intelligence, Robotics or Automation or (2) VR/AR, or both.

Moreover, **Table 2** offers a crosstabulation of AET adoption and external information/advice amongst the full sample, showing that 10.71% of the firm-year observations reporting the use of external information/advice also reported AET adoption, compared with only 5.03% among those not using external information/advice. Importantly, this table offers some preliminary insights into the potential association between both variables: The difference in AET adoption rates between firm-year observations that used external information/advice and those that did not is statistically significant ($\chi^2(1) = 93.74, p < .001$), thereby suggesting preliminary support for a positive association between using external information/advice and AET adoption.

Table 2: AET and External Information/advice over time

External information/advice	Non-AET adopter, n (%)	AET adopter, n (%)	Total, n
No	5,494 (94.97%)	291 (5.03%)	5,785
Yes	2,444 (89.29%)	293 (10.71%)	2,737
Total	**7,938 (93.15%)**	**584 (6.85%)**	**8,522**

Notes: Percentages are calculated across rows. Pearson $\chi^2(1) = 93.74$, $p < .001$. The analysis includes firm-year observations with non-missing information on both AET adoption and external information/advice.

Taken together, **Table 1** and **Table 2** show important characteristics of, and patterns in, the sample, whereby firms in our sample are more likely to use external information/advice, and those who do show a higher tendency to also be an AET adopter. Yet, what kind of advice are firms using, for what reason and from whom? These questions are intriguing from both a theoretical and empirical lens as they offer further nuance to the association between using external information/advice and AET adoption. The LSBS contains two relevant items in this regard. First, there is item K4_5 which exists across our studied time period of 2018-2021: "*Reason for using information/advice – UK*." Respondents could then answer out of 19 options. Second, the LSBS includes item K6_7 "*Who received information/advice from – UK*", which includes over 20 different possible sources ranging from Accountants and Banks to Chambers of Commerce and universities. Notable, these items are only asked to those firms which were using external information/advice, meaning that they cannot be used as moderating variables, as further detailed below, but rather as sample restrictions to offer further nuance to our findings.

In this report, we focus on three possible reasons for using external information/advice, namely, (1) Improving efficiency/ productivity, (2) E-commerce/ Technology and (3) Innovation, as these reasons closely align with AET adoption. Other reasons captured by the LSBS, such as legal issues or workplace pensions, are less directly relevant to the focus of this study and are therefore not considered further here. Similarly, despite the broad spectrum of possible sources for external information/advice, we focus our attention here on: (1) Government Support (chamber of commerce, GOV website and local council/authority); (2) Professional Advisers (accountant; consultant/general business adviser; financial adviser; solicitor/ lawyer) and (3) Business & Education (business networks/trade associations; local enterprise partnerships; universities/ education sector). This grouping distinguishes between public and quasi-public institutional support, market-based professional expertise, and knowledge accessed through educational networks. We focus on these three channels because they represent formal and realistic external knowledge sources available to UK SMEs.

Table 3 illustrates both the reasons for using external information/advice and the sources of it. Among the former, almost 13% of firm-year observations sought external information/advice for reasons pertaining to improving business efficiency/ productivity; this is particularly interesting given our additional focus on the potential productivity implications of AET adoption and highlights an important motive behind our key independent variable. The dominant source of external information/advice pertains to professional advisers (over two-thirds of firm-year observations), which shows that firms take this activity seriously. Overall, the table suggests that firms predominantly obtain external knowledge through professional advisers, while efficiency/productivity improvement represents the most prevalent motive among the reasons for using external information/advice considered here.

Table 3: External Information/Advice: Reasons and Sources

	n	**%**
Selected reasons for using external information/advice		
Improving business efficiency/productivity	355	12.97
E-commerce/technology	218	7.96
Innovation	136	4.97
Sources of external information/advice		
Government support	373	13.63
Professional advisers	1,844	67.37
Business networks/education sources	550	20.09

Notes: Table reports frequencies and percentages among firm-year observations which sought external information/advice (*N* = 2,737).

4.3 Variables

4.3.1 Dependent and independent variables

The main *dependent variable* in this report is the adoption of advanced and emerging technologies (AET). In line with Velez-Ospina & Breslin (2025), we constructed a binary variable ("AET") coded "1" where a firm reported using either (1) artificial intelligence, robotics or automation, (2) virtual or augmented reality (VR/AR), or both, and "0" where the firm reported using neither technology category. Across our sample, 590 firm-year observations (6.76%) were classified as AET adopters, while 8,142 (93.24%) were classified as non-adopters. The low rate of adoption reflects the early stages of diffusion of these technologies among UK SMEs, and more recent data may point to a greater uptake, but this is merely assumed, as our empirical data stops in 2021.

While for our main model, we coded and used AET adoption as one variable, thereby combining two different types of technologies, we also coded variables “AI” and “VR/AR” separately for the purpose of the robustness checks, as further detailed below. For the AI variable, a value of “1” indicates that the firm adopted artificial intelligence, robotics or automation, while a value of “0” indicates it did not. Similarly, for the VR/AR variable, a value of “1” indicates adoption of virtual or augmented reality, while a value of “0” indicates non-adoption. Interestingly, across the sample, AI/robotics/automation was overall more prevalent than VR/AR, which aligns with anecdotal evidence highlighting the increased adoption of especially AI-related tools amongst firms in general, and SMEs in particular.

Moreover, the main *independent variable* in this report measures whether a firm used external information/advice, or not. In the LSBS, respondents have three response options to answer this question, namely ‘yes’, ‘no’ and ‘don’t know’. Based on this, we constructed a binary variable (“extknow”), coded “1” where a firm reported having used external information or knowledge and “0” where it reported not having done so. Responses in the “don't know” category were treated as missing. Across our final sample, information on this measure is available for 8,522 firm-year observations, of which almost one-third (32.12%) did use external information/advice.

4.3.2 Productivity (supplementary analysis)

Beyond examining the association between using external knowledge/information and AET adoption amongst UK SMEs, this report further seeks to understand the likely productivity implications arising from AET adoption as these insights are of particular interest to policy makers. Thus, we coded an additional outcome variable for the supplementary analysis, namely labour productivity. The LSBS does not contain a direct measure of productivity, requiring us to construct one, whereby we followed the approach taken by Liñares-Zegarra and Wilson (2025). Specifically, we measured labour productivity as turnover per employee. Turnover was based on item P1 in the LSBS, which asked respondents to report the approximate turnover of their business in the past 12 months across all UK sites. Employment was based on LSBS item A2, capturing the number of employees currently on the firm's payroll in the UK, excluding owners and partners, and item A2A, capturing the number of working owners and partners. We combined these measures to capture the total number of individuals working in the firm and divided annual turnover by this measure to obtain turnover per employee. Given the substantial right-skewness of the resulting variable, we applied a natural logarithmic transformation and used the resulting logged measure of labour productivity in our supplementary analyses. Observations reporting zero turnover were excluded from the logged productivity measure because the natural logarithm of zero is undefined.

4.3.3 Control variables

We include several control variables which may further explain SMEs’ adoption of AET. First, as previously identified by Velez-Ospina & Breslin (2025), whether firms invest into *R&D* is relevant for their AET adoption, which is why we include a control variable, indicating whether (or not) a firm invested in R&D. Notably, this variable is based on item J5 in the LSBS, asked to Cohort C firms only, and available as a dichotomous variable, whereby a value of ‘1’ indicates that the firm did invest in R&D over the last three years and a value of ‘0’ indicates the firm did not make any R&D investments over the past three years. Second and related, we control for firms’ *exporting* activities, adding a variable indicating whether a firm exported (‘1’) or not (‘0’). Firms which export may be more likely to adopt AET due to their international market access, which offers important knowledge and learning opportunities alongside additional income streams (see also Juergensen et al., 2024).

We control for other relevant firm characteristics, including *firm size*, *age*, *legal form, location* and *turnover*. *Firm size* is based on two LSBS items: A2 which indicates how many employees are currently on the firm’s payroll in the UK, excluding owners and partners, and A2A which asks about how many working owners and partners there are (in addition to the employees mentioned). The size variable is therefore calculated by combining A2 and A2A to account for all employees on the payroll and working owners/partners; the variable is then log transformed. *Firm age* is based on LSBS item A6 which is a categorical variable of firm age categories ranging from ‘less than a year’ to ‘more than 20 years’. Firms’ legal form is a categorical variable, based on LSBS item A5SUM, and

includes four categories, thereby taking on the following values: ‘sole proprietorship’ (‘1’); ‘company’ (‘2’), partnership (‘3’) and other (‘4’).

We further account for firms’ location within the UK by including a variable, indicating whether a firm is located in an urban area (‘0’) or a rural area (‘1’). Where firms are located can influence the adoption of AET, whereby urban firms may benefit from greater proximity to networks and digital infrastructure relevant for AET adoption, which is why we control for this variable. Similarly, AET adoption may be partially driven by available financial resources and funds, which is why we also control for firms’ annual turnover. This variable is based on LSBS item P1B which is a categorial variable, consisting of ten categories, ranging from *less than £85,000* (‘1’) to *£25m or more* (‘10’). Using this item over P1 allowed for less observations to be dropped in the main analysis.

Additionally, given that AET adoption implies medium- to longer-term investments, we account for firms’ expected future performance by controlling for indicators capturing whether firms expect to grow or shrink, making use of LSBS item EXPGROW. These variables allow us to account for differences in firms’ anticipated growth trajectories that may also be associated with their propensity to invest in AET. The first variable is coded ‘1’ where a firm reports expecting to grow and ‘0’ otherwise. The second variable is coded ‘1’ where a firm expects to shrink and ‘0’ otherwise.

Finally, beyond these firm characteristics, we also control for relevant ownership and leadership characteristics. First, we account for *family ownership* using a binary variable, based on LSBS item A12, indicating whether a firm identifies as a family-owned business (‘1’) or not (‘0’). Second, we control for whether a firm is *women-led*, using a binary indicator distinguishing women-led firms (‘1’) from other firms (‘0’). Third, based on LSBS item A19, we account for whether a firm is *ethnic minority-led*, meaning that at least one person amongst the owners/ partners identifies as ethnic minority, with a value of ‘1’ identifying ethnic minority-led firms and ‘0’ otherwise. All models include survey-year effects to account for common temporal differences across the 2018-2021 survey waves, as well as sector effects to account for systematic differences in AET adoption across industries.

4.4 Analytical Methods

The analysis was conducted in STATA 19.5 as the primary statistical package. To examine the association between firms’ use of external information/advice and AET adoption, we estimated logistic regression models using the pooled firm-year observations across the 2018-2021 LSBS waves. This approach was chosen for the following reasons: Pooling the available observations allowed us to exploit information across all four survey years for which the AET variable was consistently available, while accounting for the fact that the resulting dataset represents a highly unbalanced panel, whereby most firms were observed only once. This poses both empirical and theoretical challenges for panel models, especially those relying on within-firm variation, making a pooled regression analysis the preferable choice here. Additionally, given the binary nature of our dependent variable, indicating whether firms adopted AET or not, a logistic model was chosen. Survey-year effects were included to account for common temporal differences in AET adoption across the four included survey waves, and standard errors were clustered at the firm-level to account for the potential non-independence of repeated observations from the same firm.

Additionally, to reduce the risk that the relationship between external information/advice and AET adoption is driven by systematic differences between those firms which use external information/advice and those which do not (i.e., users versus non-users), propensity score matching (PSM) was employed. This is in line with previous studies using similar data (Velez-Ospina & Breslin, 2025). This is an important additional step because the use of external information/advice may not be randomly assigned; for example, firms that use such information/advice may differ from non-users in observable characteristics that are themselves associated with AET adoption (such as size, location, etc.). We therefore estimated firms’ propensity to use external information/advice based on the observable firm characteristics included in our analysis (i.e., firm size, age, turnover, R&D activity, ownership characteristics, exporting, growth expectations, legal status, rural location, sector and survey year). Using the resulting propensity scores, users of external information/advice were

then matched with comparable non-users, thereby improving the balance of observable characteristics between the two groups. Details on this are available in the Appendix. We subsequently re-estimated our main model using the matched sample, as further detailed below, to assess whether the association between (1) external information/advice and (2) AET adoption remains. Notably, as PSM can only account for differences in observed characteristics, this additional analysis is to be interpreted as a robustness test rather than as establishing a causal effect. Finally, several additional robustness checks were conducted, as further detailed below.

4.5 Limitations

As with any report or academic study, several limitations should be considered when interpreting the findings reported below. In this case, they largely arise from the design and structure of the LSBS.

First, despite being designed as a longitudinal survey, a substantial proportion of firms in our sub-sample of the LSBS participated only once. Thus, we were unable to meaningfully exploit the panel structure of the data using longitudinal specifications in STATA. Ideally, repeated observations of the same firms would have allowed us to examine within-firm changes in the use of external information/advice and AET adoption over time and to employ lagged explanatory variables to better establish temporal ordering and address endogeneity concerns (e.g., see Love, Roper & Vahter, 2014). However, the relatively small number of firms with observations across multiple relevant survey waves made such an approach unsuitable for the present analysis. We therefore used pooled regression models instead, which allowed us to exploit the available firm-year observations and examine differences across firms over the studied time period, while clustering standard errors at the firm-level to account for repeated observations.

Second and related, the nature of the data meant that endogeneity could not be formally addressed through conventional means, such as the use of time lags or fixed-effects specifications (D'Angelo, Ganotakis & Love, 2020). We therefore sought to mitigate concerns around endogeneity arising from omitted variable bias by including a broad set of relevant control variables in our model. Endogeneity concerns may also arise due to reverse causality, whereby external information/advice may facilitate firms' AET adoption and AET adopting firms may be more likely to seek external information/advice. The propensity score matching analysis provides an additional robustness check in this regard by improving comparability between users and non-users of external information/advice based on observed characteristics. The persistence of the positive association within the matched sample, as further explained below, strengthens confidence in the robustness of the findings presented below. However, PSM cannot fully account for selection based on *unobserved* characteristics and therefore does not establish a causal relationship. Thus, the results below should be interpreted as robust associations rather than causal effects.

Third, our analysis is based on a relatively small subsample of the overall LSBS because AET adoption, as our dependent variable, was only asked of firms belonging to Cohort C. This restricted the available analytical sample and may limit the extent to which the findings can be generalised to the wider population. Nevertheless, the available Cohort C observations provided a relevant sample through which to examine the relationship between external information/advice and AET adoption. Specifically, conducting the analysis using survey weights as part of our robustness checks and postestimation analysis provided further support for the robustness of this relationship. Moreover, due to changes in the LSBS questionnaire, AET adoption, as operationalised here, could only be examined up to 2021 (see also Velez-Ospina & Breslin, 2025). Future research using more recent data could therefore examine whether the relationship identified here persists, as these technologies have likely become much more widely diffused among UK firms in general, and SMEs in particular.

Finally, an important objective of the study was to understand the nuances underlying the association between external information/advice and AET adoption. In particular, both firms' (1) underlying reasons for using external information/advice and (2) its source may matter and explain potential differences amongst firms. However, the LSBS only asks the relevant reason and source questions of firms that have already reported using external information/advice. Consequently, these

characteristics could not be observed for non-users, meaning that a formal moderation analysis was not possible. Our subsample analyses below provide some preliminary insights by examining whether particular reasons and sources are associated with AET adoption among those firms which used external information/advice. Overall, the findings presented next should be interpreted in view of these methodological limitations and as an *association* between external information/advice and AET adoption.

5. Findings

5.1 Descriptive statistics

Table 4 reports the descriptive statistics of all main variables used in the analysis. Beyond illustrating descriptive statistics on our main variables (AET; external information/advice), as previously discussed, the table further shows meaningful descriptives of our control variables. In particular, the variable for firm size merits attention. For this variable, we report here raw employee counts, showing a maximum number of employees in a giver firm year of 428, which is above the standard SME threshold of 249 employee (DBT, 2024). As previously noted, we decided to keep firms which outgrew this SME threshold as these observations are meaningful given that the LSBS retains cases that were at some point SMEs. As shown later on, these firms do not alter our main results on the association between using external knowledge/information and AET adoption.

Table 4: Descriptive statistics

	n	Mean	SD	Min	Max
AET	8732	0.068	0.251	0	1
extknow	8522	0.321	0.467	0	1
size	8128	24.565	37.630	1	428
agecat	8703	3.072	1.044	1	4
rd	8619	0.263	0.440	0	1
Women	8318	0.176	0.381	0	1
Turnover	7761	3.921	2.344	1	10
ExpGrow	8247	0.493	0.500	0	1
ExpShrink	8247	0.101	0.302	0	1
Family	8714	0.702	0.458	0	1
Ethnic	8028	0.082	0.274	0	1
Exporting	8685	0.265	0.441	0	1
SECTOR	8732	2.46	0.993	1	4
rural	8517	0.288	0.453	0	1
legal	8732	2.072	0.620	1	4

***Notes*:** The number of observations varies across variables due to missing values.

In addition to the descriptive statistics, Pairwise Pearson correlations between the variables included in the analysis are reported in Appendix A. We use pairwise correlations to retain the maximum number of available observations for each correlation, given that the extent of missing data differs across variables, as previously noted. As shown in Appendix A, the correlation coefficients are generally modest in magnitude, therefore suggesting no immediate concerns regarding high correlations among the explanatory and control variables.

To further formally assess potential multicollinearity, however, we calculate variance inflation factors (VIFs) for the explanatory and control variables included in our main model, with the full results reported in Appendix B. The mean VIF is 1.683, while the highest individual VIF is 3.504. Both values are well below commonly accepted thresholds of an average VIF of six and an individual VIF of ten (O'Brien, 2007), overall suggesting no collinearity problems with our estimations, which are further detailed next alongside detailed explanations of our core findings.

5.2 External information/advice and AET adoption

The results for the main analysis, based on a pooled logistic regression and PSM, are presented in **Table 5** below.

Table 5: Main Analysis results (Pooled logistic regression for AET adoption)

	(1)	(2)	(3)
	Controls	Full	Full (matched)
External information/advice		**0.447*** **	**0.499*** **
		(0.104)	**(0.114)**
Firm characteristics			
Size (log)	0.069	0.063	0.079
	(0.068)	(0.069)	(0.074)
Age (bands)	-0.120*	-0.118*	-0.166*
	(0.056)	(0.056)	(0.065)
Conducts R&D	1.044***	0.980***	0.950***
	(0.118)	(0.119)	(0.130)
Exporting	0.497***	0.485***	0.497***
	(0.116)	(0.116)	(0.128)
Women-led	-0.168	-0.179	-0.073
	(0.165)	(0.165)	(0.185)
Ethnic minority-led	0.376*	0.389*	0.404*
	(0.164)	(0.165)	(0.183)
Family-owned	0.124	0.126	0.066
	(0.124)	(0.124)	(0.136)
Rural location	-0.011	-0.015	-0.109
	(0.123)	(0.123)	(0.145)
Expects growth	-0.002	-0.031	-0.067
	(0.111)	(0.112)	(0.127)
Expects shrink	0.065	0.031	-0.120
	(0.177)	(0.177)	(0.211)
Sector (base ABCDEF – Production and construction)			
GHI – Transport, retail, food service/accommodation	-0.582***	-0.584***	-0.488*
	(0.171)	(0.171)	(0.195)
JKLMN – Business services	0.537***	0.505***	0.602***
	(0.138)	(0.138)	(0.157)
PQRS – Other services	-0.102	-0.150	-0.138
	(0.237)	(0.237)	(0.278)
Turnover (base Less than £85,000)			
£85,000 – £249,999	0.137	0.112	0.184
	(0.189)	(0.188)	(0.235)
£250,000 – £499,999	-0.150	-0.170	-0.004
	(0.251)	(0.251)	(0.290)
£500,000 – £999,999	-0.097	-0.142	-0.261
	(0.257)	(0.257)	(0.309)
£1m – £1.99m	0.057	0.017	0.047

	(0.253)	(0.254)	(0.291)
£2m – £4.99m	0.344	0.284	0.273
	(0.272)	(0.273)	(0.311)
£5m – £9.99m	0.557	0.481	0.501
	(0.293)	(0.294)	(0.331)
£10m – £14.99m	0.452	0.370	0.426
	(0.362)	(0.362)	(0.396)
£15m – £24.99m	0.924*	0.844*	0.901*
	(0.377)	(0.376)	(0.410)
£25m or more	1.055**	0.960*	1.049*
	(0.390)	(0.391)	(0.425)
Legal form (ref. Sole proprietorship)			
Company	-0.022	-0.027	-0.143
	(0.224)	(0.225)	(0.294)
Partnership	-0.057	-0.084	-0.098
	(0.309)	(0.310)	(0.385)
Other	-0.096	-0.129	-0.250
	(0.415)	(0.421)	(0.489)
Survey year (ref. 2018)			
2019	0.614***	0.619***	0.641***
	(0.128)	(0.128)	(0.145)
2020	0.422**	0.432**	0.545**
	(0.149)	(0.150)	(0.172)
2021	0.748***	0.744***	0.790***
	(0.131)	(0.130)	(0.147)
Constant	-3.687***	-3.742***	-3.614***
	(0.339)	(0.339)	(0.441)
Average marginal effect of external knowledge		0.028***	0.039***
Observations	6,378	6,378	4,072
Log likelihood	-1,514.410	-1,504.947	-1,135.924
Wald chi2	356.681	370.732	254.444

***Notes*:** Dependent variable is AET. Standard errors, clustered at firm level (SERIAL), in parentheses. All models include year dummies. Average marginal effects are expressed as changes in the probability of adoption. * p<0.05, ** p<0.01, *** p<0.001.

Model 1 in **Table 5** includes the control variables only and provides the baseline specification. The results indicate that several firm characteristics are significantly associated with AET adoption. In particular, firms undertaking R&D and exporting are more likely to adopt AET. These findings are consistent with prior research (see Velez-Ospina & Breslin, 2025). Notably also, the results reveal significant sectoral differences in AET adoption. In particular, relative to firms operating in production and construction, firms in transport, retail and food services are significantly less likely to adopt AET, whereas firms in business services are significantly more likely to do so. These findings point to meaningful variation in AET adoption across sectors and reinforce the importance of accounting for sectoral differences in the analysis. Significant differences across survey years are also observed, indicating temporal variation in AET adoption over the period examined.

Moreover, *Model 2* introduces the use of external information/advice as the main explanatory variable. As expected, the coefficient for external information/advice is positive and statistically significant ($\beta = 0.447$, $p < 0.001$), indicating a positive association between the use of external information/advice and AET adoption after controlling for the other firm characteristics. Notably, the average marginal effect is 0.028 ($p < 0.001$), suggesting that firms using external information/advice

have, on average, a 2.8 percentage-point higher predicted probability of adopting AET than firms that do not, holding constant the other variables. Overall, these findings provide support for a positive association between the use of external information/advice and AET adoption, which is in line with our aforementioned theoretical argumentation.

Importantly, **Table 5** also includes *Model 3* which re-estimates the full model using the propensity-score-matched sample to account for observable differences between firms that use and do not use external information/advice. We conducted propensity score matching to reduce the risk of heterogeneity amongst observable characteristics across the external knowledge seekers and non-seeker groups of firms (e.g., see also Velez-Ospina & Breslin, 2025). Appendix C *Table C1* show the results for the logistic regression conducted in this procedure using the *psmatch2* command in STATA. The variables in the regression are the parameters we used to create the matched sample. The propensity model in Appendix C *Table C1* indicates that advice seeking is mostly predicted by R&D activity (0.686, $p<0.001$), the largest single effect in the model. This effect is followed by expected growth, firm size, and turnover. Sector also shows interesting effects, where firms in business services were more likely to seek external advice than those in production and construction sectors. Furthermore, Appendix C *Figure C1* shows the distribution of propensity scores between the treated and control groups, with similar bars mirroring each other along the x axis. Notably, only one case fell off common support. For both groups, their propensity scores overlap substantially across the distribution, thus confirming sufficient support for conduction propensity score matching.

Appendix C *Table C2* further shows covariate balance across the selected specifications. There were significant differences between users and non-users, before matching. Users were R&D active (standardised bias 41%, the largest difference), bigger by workforce (35.7% std bias) and turnover (35.7%). They were also more growth oriented (20.5%), more were private limited companies (15.5%), and were more frequently exporting (18.4%). Less belonged in the transport, retail, and hospitality sectors (-11.9%); fewer were family-owned firms (-16%). As those characteristics were independently predicting adoption, the unmatched adoption gap conflates the effect of information/advice using with compositional differences. Matching removes that in the observables, and the effect of external information/advice using 4.27 pp survives (Appendix C *Table C3*). This is roughly a 60% increase relative to the 6.8% adoption rate (mean AET).

Overall, as shown in *Model 3* in **Table 5**, the association between external information/advice and AET adoption remains positive and statistically significant in the matched sample ($\beta = 0.499$, $p < 0.001$). The average marginal effect is 0.039 ($p < 0.001$), indicating that the predicted probability of AET adoption is, on average, approximately 3.9 percentage points higher among firms using external information/advice than among otherwise comparable matched firms that do not. Thus, the direction and statistical significance of the relationship therefore remain consistent after matching, providing additional evidence of the robustness of the main finding to observable differences between users and non-users of external information/advice. The full marginal effects tables for *Model 2* and *Model 3* are reported in Appendix D.

5.3 The reason and source for seeking external information/advice

Moreover, we are interested in understanding the role of the underlying reason for using external information/advice and the sources of it which we further investigate empirically, also using logistic regression models. Notably, testing these characteristics as moderators of the association between external information/advice and AET adoption is not possible due to LSBS design, as these questions are only asked to firms which reported to use external information/advice. We therefore conducted a subsample analysis restricted to these firms to examine whether variation in the reasons for using external information/advice and the sources from which it is obtained is associated with the likelihood of AET adoption.

As illustrated in **Table 6** below, AET adoption remains the dependent variable, whereby we tested (1) the reason in *Model 1* as the independent variable (distinguishing between Efficiency; Technology and Innovation), and the source of advice in *Model 2* (distinguishing between Government support; Professional services and Business education). Notably, both models include the same set of control variables as reported in **Table 5**, overall allowing us to examine whether particular reasons for, and sources of, external information/advice are associated with AET adoption among firms that use such information/advice.

Table 6: Reasons for and sources of external information/advice and AET adoption

	(1)	(2)
Types of advice sought		
Efficiency	**0.518****	
	(0.192)	
Technology	-0.117	
	(0.246)	
Innovation	**0.807****	
	(0.258)	
Sources of advice		
Government support		0.088
		(0.212)
Professional services		**0.366***
		(0.172)
Business education		**0.420***
		(0.191)
Firm characteristics		
Size (log)	0.021	0.014
	(0.095)	(0.094)
Age (bands)	-0.150	-0.149
	(0.085)	(0.085)
R&D	0.886***	0.957***
	(0.171)	(0.170)
Exporting	0.652***	0.621***
	(0.167)	(0.167)
Women-led	-0.250	-0.256
	(0.252)	(0.253)
Ethnic minority-led	0.243	0.230
	(0.250)	(0.249)

Family-owned	0.008	-0.028
	(0.179)	(0.177)
Rural location	-0.064	-0.038
	(0.185)	(0.182)
Expects growth	-0.112	-0.113
	(0.169)	(0.168)
Expects shrink	0.108	0.116
	(0.259)	(0.260)
Sector (base ABCDEF – Production and construction)		
GHI – Transport, retail, food service/accommodation	-0.553*	-0.585*
	(0.254)	(0.257)
JKLMN – Business services	0.470*	0.428*
	(0.201)	(0.203)
PQRS – Other services	-0.180	-0.218
	(0.373)	(0.370)
Turnover (base Less than £85,000)		
£85,000 – £249,999	0.129	0.078
	(0.305)	(0.301)
£250,000 – £499,999	0.007	-0.010
	(0.384)	(0.378)
£500,000 – £999,999	-0.324	-0.356
	(0.399)	(0.393)
£1m – £1.99m	0.055	0.045
	(0.376)	(0.365)
£2m – £4.99m	0.291	0.274
	(0.396)	(0.392)
£5m – £9.99m	0.515	0.471
	(0.426)	(0.414)
£10m – £14.99m	0.132	0.059
	(0.510)	(0.507)
£15m – £24.99m	1.038*	0.964
	(0.522)	(0.514)
£25m or more	1.023	1.046
	(0.549)	(0.538)
Legal form (base Sole proprietorship)		
Company	0.074	0.002
	(0.379)	(0.370)
Partnership	0.212	0.080
	(0.474)	(0.468)
Other	-0.088	-0.028
	(0.634)	(0.626)
Survey year (base 2018)		
2019	0.389*	0.424*
	(0.192)	(0.191)

2020	0.179	0.199
	(0.227)	(0.227)
2021	0.636***	0.670***
	(0.189)	(0.189)
Constant	-3.065***	-3.180***
	(0.581)	(0.603)
Observations	2,037	2,037
Log likelihood	-640.956	-646.583
Wald chi2	175.665	161.987

Notes: Dependent variable is AET **adoption**. Both models are estimated on advice-seeking firms only since the **reason** and source measures are defined for that subgroup. Standard errors, clustered at firm level (SERIAL), in parentheses. Both models include year dummies. * p<0.05, ** p<0.01, *** p<0.001**.**

In *Model 1*, both Efficiency and Innovation are positive and significant. Specifically, using external information/advice to improve efficiency is positively associated with AET adoption ($\beta = 0.518$, $p < 0.01$). The corresponding average marginal effect, presented in **Table 7** below, indicates an approximately 4.8 percentage-point higher predicted probability of AET adoption among firms reporting this reason. Moreover, the association is particularly pronounced for firms using external information/advice for Innovation purposes ($\beta = 0.807$, $p < 0.01$), corresponding to an approximately 7.5 percentage-point higher predicted probability of AET adoption. In contrast, using external information/advice for Technology/e-commerce purposes is not significantly associated with AET adoption. Together, these findings suggest that the underlying motivation for using external information/advice matters, with *innovation* in particular being associated with a higher likelihood of AET adoption among firms using external information/advice.

Model 2 in **Table 6** considers the sources firms obtain external information/advice from. As shown in **Table 6** and **Table 7**, the use of professional services is positively and significantly associated with AET adoption ($\beta = 0.366$, $p < 0.05$), with an average marginal effect of approximately 3.4 percentage points. Similarly, obtaining information/advice from business and education sources is positively associated with AET adoption ($\beta = 0.420$, $p < 0.05$), corresponding to an approximately 3.9 percentage-point higher predicted probability of adoption. Notably, government support is not significantly associated with AET adoption, which raises some useful implications for policy makers as further discussed later. In terms of control variables, R&D and exporting remain highly relevant which is in line with previous research on AET adoption (see Velez-Ospona & Breslin, 2025).

Overall, these results indicate that not only the use of external information/advice, but also the reasons for which it is used and the sources from which it is obtained, are relevant for understanding differences in AET adoption among firms.

Table 7: Average marginal effects

	dy/dx	Std. err.	z	p
Motivation of advice (*Model 1*)				
Efficiency	0.048	0.018	2.70	0.007
Technology	-0.011	0.023	-0.48	0.635
Innovation	0.075	0.024	3.13	0.002
Sources of advice (*Model 2*)				
Government support	0.008	0.020	0.41	0.679
Professional services	0.034	0.016	2.12	0.034
Business education	0.039	0.018	2.18	0.030

5.4 AET adoption and productivity

The final section of this report depicts a supplementary analysis of the labour productivity implications of AET adoption amongst our sample. Our primary objective here is to examine whether AET adoption is associated with productivity among UK SMEs. As stated in the methodology section, the focus of this analysis is labour productivity, measured as the total turnover per employee (see: Liñares-Zegarra & Wilson, 2025). Notably, the continuous variable for turnover (LSBS item P1) had a large number of missing values, reducing the sample to 5,480 observations. We conducted standard linear regression OLS using STATA on a raw sample and a propensity score matched sample of AET adopters and non-adopters.

Table 8 below shows labour productivity in its natural logarithmic expression as the dependent variable, whereby we provide the controls and baseline specification in *Model 1*; we then introduce AET adoption as the main explanatory variable in *Model 2;* and finally estimate the effect of AET adoption in the matched sample in *Model 3*. Notably, both *Model 2* and *Model 3* include the same set of control variables, overall allowing us to examine the productivity implications of AET adoption for labour productivity among sample firms.

Table 8. Supplementary analysis
(Pooled OLS regression for labour productivity).

	(1)	(2)	(3)
	Controls	Full	Full/matched
AET		**0.102***	**0.093**
		(0.050)	**(0.059)**
External information/advice	**0.098*****	**0.094****	**0.140***
	(0.029)	**(0.029)**	**(0.059)**
Size (log)	-0.012	-0.014	0.011
	(0.013)	(0.013)	(0.024)
Age (bands)	0.117***	0.118***	0.117***
	(0.015)	(0.015)	(0.032)
Conducts R&D	0.126***	0.117***	0.058
	(0.034)	(0.035)	(0.065)
Exporting	0.370***	0.365***	0.365***
	(0.034)	(0.034)	(0.065)
Women-led	-0.141***	-0.139***	-0.194
	(0.040)	(0.040)	(0.100)
Ethnic minority-led	0.011	0.007	-0.060
	(0.060)	(0.060)	(0.115)
Family-owned	-0.152***	-0.153***	-0.061
	(0.036)	(0.036)	(0.074)
Rural location	-0.065*	-0.064	-0.077
	(0.033)	(0.033)	(0.067)
Expects growth	-0.080**	-0.080**	-0.036
	(0.030)	(0.030)	(0.059)
Expects contraction	0.031	0.031	-0.008
	(0.046)	(0.046)	(0.104)
Sector (ref. ABCDEF – Production and construction)			
GHI – Transport, retail and food services	-0.056	-0.053	0.055
	(0.040)	(0.040)	(0.097)
JKLMN – Business services	-0.311***	-0.315***	-0.309***
	(0.038)	(0.038)	(0.075)

PQRS – Other services	-0.891***	-0.890***	-0.745***
	(0.054)	(0.054)	(0.138)
Legal form (ref. Sole proprietorship)			
Company	0.527***	0.529***	0.599***
	(0.051)	(0.051)	(0.159)
Partnership	0.303***	0.303***	0.289
	(0.069)	(0.069)	(0.203)
Other	0.201	0.205	0.620*
	(0.125)	(0.125)	(0.252)
Survey year (ref. 2018)			
2019	0.047	0.044	0.225**
	(0.033)	(0.033)	(0.074)
2020	-0.188***	-0.191***	0.068
	(0.043)	(0.043)	(0.096)
2021	-0.085*	-0.089*	-0.010
	(0.035)	(0.035)	(0.075)
Constant	10.494***	10.493***	10.177***
	(0.082)	(0.082)	(0.218)
Observations	5,480	5,480	1,391
R-squared	0.190	0.191	0.193

Notes: Dependent variable: log labour productivity (turnover per employee). OLS estimates. Model 3 conducted on the propensity score matched sample (three nearest neighbours, matched-control weights applied). Standard errors, clustered at firm level (SERIAL), in parentheses. All models include year dummies. * p<0.05, ** p<0.01, *** p<0.001.

Model 1 in **Table 8** includes the control variables only and provides the baseline specification. The results indicate that a few firm characteristics are significantly associated with labour productivity. Interestingly, firms using external knowledge are more productive, and the effect is consistently positive and significant across all three models in **Table 8**. The results indicate a similar pattern for exporting and age, whereby older firms and those engaging in exporting are more productive. These findings are consistent with prior research (Cherchem et al., 2026). *Model 1* also shows R&D (β= 0.126, p < 0.001) is associated with labour productivity, while women-led (β= -0.141, p < 0.001) and family businesses (β= -0.152, p < 0.001) show significantly lower productivity. In particular, the women-led gap persists despite controlling for size and sector. A plausible explanation for its negative association with labour productivity could be access to finance (Rose, 2019), or further sectoral differences masked behind our broad sector measures. Sectoral effects indicate that compared to production and construction, firms operating in the business services and other services are significantly less productive in labour terms. Furthermore, year variations in productivity show a decrease in productivity during 2020, possibly reflecting the wider socio-economic effects of the COVID-19 pandemic (Juergensen, Guimón & Narula, 2020).

Additionally, *Model 2* in **Table 8** introduces AET adoption to estimate the productivity gains in firms that engage in AET. The results show there is a positive and significant association between AET adoption and labour productivity (β = 0.102, p < 0.05). Firms that adopt AET are roughly 10% more productive, a positive association that does not survive once the sample is matched, however (see *Model 3*). The association between using external information/advice and productivity is positive and significant (β 0.094, p < 0.01) and is essentially independent of AET. This is an important result, considering the previous section which analysed the effect of external information/advice on AET adoption. In sum, external information and advice sourcing is positively associated with AET adoption (**Table 5**) and with labour productivity (*Model 2*, **Table 8**). Finally, the introduction of AET in *Model 2* attenuates the effect on R&D slightly (β= 0.117, p < 0.001).

Furthermore, *Model 3* in **Table 8** re-estimates the effect of AET adoption on labour productivity using a propensity-score-matched sample to account for observable differences between firms that adopt and do not adopt AET. Notably, the effect of AET adoption on labour productivity is lost, once we match the sample ($\beta = 0.093$, $p > 0.05$). In contrast, the positive effect of external information and advice persists even after matching. In *Model 3*, firms that used external information and advice show approximately 15% higher labour productivity than those that did not ($\beta = 0.140$, $p < 0.05$).

We briefly summarise the results from the propensity score matching procedure here and the full results are available from the authors upon request. To create the matched weight, we applied propensity score matching with AET adoption as the treatment using the *psmatch2* procedure in STATA. We estimate the propensity to adopt AET as a function of the observed characteristics specified in *Model 1*, matching each adopting firm to its three nearest non-adopting neighbours. We estimated 1:3 instead of 1:1 given the small number of firms engaged in AET adoption (432 firms). Overall, matching achieves close balance. Of 432 adopting firms, 429 are matched within common support. The unmatched productivity gap of 0.254 log points (roughly 29%) falls to ATT = 0.069, and it is statistically indistinguishable from zero (t = 1.09).

The results from this procedure also indicate that AET adopters differ systematically form non-adopters: they are substantially more R&D active (standardised bias 72.2%), more likely to export (45.2%), and are largely concentrated in business services sector (35.5%). Beyond these initial characteristics, AET adopters are also more likely to have used external knowledge (39.5%), consistent with the association established in **Table 5**. Together, these characteristics predict labour productivity, conflating adoption with the raw composition of firms. After matching, the covariates are jointly insignificant in predicting AET adoption ($p = 0.993$). Mean standardised bias falls from 20.4 to 3.7 and R is 1.30, within the recommended threshold. Finally, these findings of the supplementary analysis should also be considered in view of the aforementioned limitations which include the small number of observations of AET adopters.

5.5 Robustness checks

We conducted several robustness checks. First, in our main analysis, we operationalised AET adoption as a single variable combining two different types of technologies: artificial intelligence, robotics or automation (AI), and virtual or augmented reality (VR/AR). To examine whether our main findings are robust across these different types of AET, we also coded AI and VR/AR as separate dependent variables. For the AI variable, a value of “1” indicates that the firm adopted artificial intelligence, robotics or automation, while a value of “0” indicates that it did not. Similarly, for the VR/AR variable, a value of “1” indicates the adoption of virtual or augmented reality, while a value of “0” indicates non-adoption.

Using the same specification as in our main model, we examine whether external information/advice is associated separately with AI adoption (*Model A*) and VR/AR adoption (*Model B*). The results are reported in Appendix E Table E1. *Model A* shows a positive and statistically significant association between external information/advice and AI adoption, while *Model B* similarly shows a positive and statistically significant association between external information/advice and VR/AR adoption. Taken together, these findings provide further support for the robustness of our main results and indicate that the positive association between external information/advice and AET adoption is evident across both underlying technology categories, rather than being attributable to only one type of AET.

Second, we tested whether our findings remain robust, when using an alternative model specification. While our main analysis uses logistic regression due to the binary nature of AET adoption, we re-estimated the main model using a probit specification. Thus, we could test whether the identified association between external information/advice and AET adoption is sensitive to the choice of binary response model. The results, reported in Appendix E Table E2, remain consistent with our main findings: External information/advice is positively and statistically significantly associated with AET adoption – also, when using a probit model.

Third and finally, we examined whether our findings remain robust when restricting the analytical sample to SMEs, as defined by the conventional employment-based threshold of 249 (i.e., <250) employees. As previously explained, while our main analysis does not impose such an upper firm-size restriction, we re-estimated our main model using only firm-year observations with fewer than 250 employees, i.e., <250 employees. This enabled us to assess whether the identified association between external information/advice and AET adoption specifically applies to SMEs. The results, shown in Table E3 in the Appendix, remain consistent with our main findings: External information/advice is positively and statistically significantly associated with AET adoption. Notably, the number of observations reduces only marginally, namely from 6,378 in our main model to 6,374 in the size-restricted sub-sample. This confirms that our main findings are not attributable to the inclusion of larger firms in the main model.

Key Insight

There is a positive and statistically significant association between the use of external information/advice and AET adoption amongst UK SMEs. Among firms using external information/advice, the association is particularly pronounced when advice is used for innovation and efficiency purposes, while professional services and business/education sources are also positively associated with AET adoption.

6. Conclusions and Recommendations

6.1 Summary of Key Findings

The ongoing diffusion of advanced and emerging technologies (AET), including artificial intelligence, have ignited important debates amongst policy makers, academics and business managers due to their wider socio-economic implications which are yet to be fully understood. While AET have been mostly associated with large, multinational corporations, there has been increased focus on how these technologies are being used by smaller firms, including small- and medium-sized enterprise (SMEs). Since the start of the decade, SMEs have been found to be catching up with larger firms in adopting certain digital technologies more broadly, such as social media and cloud computing services; yet, many SMEs continue to lack the resources and skills needed to fully exploit these technologies' potential (OECD, 2023). Importantly, AET are somewhat even more advanced in their capabilities and transformative potential, but less is known about AET uptake in SMEs to date, despite some relevant and growing research in this field (e.g., Anderson & McKenzie, 2022; Czarnitzki et al., 2023; Jibril & Roper, 2025; Lee et al., 2022; Velez-Ospina & Breslin, 2025).

The purpose of this research report was to examine the role of external knowledge, including information and advice, from external stakeholders on AET uptake in UK SMEs. Accessing such external information and advice, e.g., from consultants, professional networks, or government support agencies, may encourage AET uptake amongst SMEs by providing expertise, guidance, and insights on industry 'best practice'. Specifically, through a behavioural theoretical lens (Cyert & March,1963; Gavetti et al., 2012), (1) uncertainty avoidance may explain *why* SMEs may seek external knowledge and advice in the context of AET adoption and (2) vicarious learning may help explain *how* such externally accessed knowledge and advice may lead to desirable organizational outcomes. In turn, from an open-innovation perspective (Chesbrough, 2016; Laursen & Salter, 2006), external knowledge may be an important mechanism through which SMEs may access relevant AET insights beyond their organisational boundaries. In particular, by complementing their internal knowledge base (e.g., generated through R&D), accessing external knowledge from relevant sources may enhance SMEs' ability to better evaluate and understand relatively unfamiliar technologies such as AET; this may then ultimately help with their adoption.

The empirical analyses presented here were based on data between 2018 and 2021 taken from the LSBS. Using this data, three interrelated research questions were explored, overall underpinning our main findings and conclusions as summarised here. First, we empirically examined whether the use of external knowledge, including information and advice, is associated with the adoption of AET

among UK SMEs. The findings, based on a number of statistical specifications, offer consistent support for a positive and statistically significant association between the two. However, it should be considered that during the studied period, only a small share of UK SMEs actually adopted AET, namely roughly 6.8% of the sample. Thus, while AET adoption was associated with using external knowledge, policy efforts should (1) target understanding what drives the low AET uptake amongst AET, (2) alongside facilitating SME access to relevant external networks which may encourage AET uptake. Additionally, in line with Velez-Ospina and Breslin (2025), we found R&D activity to be a consistent driver of AET adoption. Overall, policy intervention should focus on fostering external engagement in knowledge seeking activities, whilst in parallel, increasing access to sources of knowledge and advice. Considering the potential gains in competitiveness and innovation for firms, stemming from emerging technologies, policy should be geared towards addressing non-adopters' needs as well as the barriers to adoption. Policy to support AET adoption, especially in smaller and newer SMEs, which otherwise would not engage in AET adoption, could be beneficial to increase the overall capability of UK firms.

Second, this research explored how the sources and purposes of external knowledge use relate to AET adoption. Testing for three different reasons behind using external knowledge, the empirical findings suggest that (1) efficiency and (2) innovation are positive and significant reasons. In contrast, using external information/advice for technology/e-commerce purposes was not found to be significantly associated with AET adoption. Together, these findings suggest that the underlying reasons for using external information/advice matters, whereby particularly *innovation* and *efficiency* seem to be associated with a higher likelihood of AET adoption among those firms using external information/advice. In this regard, we also tested for different possible sources of external knowledge, building on previous research which highlights that some external sources may be more useful than others (e.g., see Chen, Vanhaverbeke, & Du, 2016; Du, Belderbos, Leten & Vanhaverbeke, 2025). According to the findings, the use of professional services is positively and significantly associated with AET adoption, as is obtaining information/advice from business and education sources. However, government support is not significantly associated with AET adoption, which raises some useful implications for policy makers.

In particular, the findings suggest that policies aimed at supporting AET diffusion among SMEs should consider not only whether firms have access to external information and advice, but also the sources through which such knowledge is provided and the purposes it serves. The positive associations identified for professional services and business and education sources point towards the potential value of strengthening SMEs' connections with these external knowledge providers. This could include facilitating links between SMEs and professional advisers, business networks and educational institutions as part of AET adoption support initiatives. Government-supported programmes such as *Help to Grow: Management courses* (see Small Business Charter, 2026) for example, illustrate how public support can connect SMEs with business schools and university-based expertise. At the same time, the absence of a significant association for government support (chamber of commerce, GOV website and local council/authority) in our analysis suggests a need to better understand how existing public sources of information and advice connect with SMEs' AET adoption needs, rather than assuming that the provision of government information or advice alone will suffice. Finally, the importance of innovation and efficiency motivations suggests that support for AET adoption may be particularly relevant when it is connected to firms' wider innovation activities, which is also consistent with our finding that R&D activity is a key driver of AET adoption.

Third, this research report asked whether AET adoption is associated with productivity among UK SMEs. The findings in this regard are less clear, given that in the full sample there is a significant positive association, but not in the matched sample, as previously detailed. Given that the latter is a more conservative methodological approach, the loss of statistical significance in the matched sample warrants consideration. At first glance, this may stand somewhat in contrast to previous research which has established a link between some form of AET adoption and productivity gains (e.g., Czarnitzki et al., 2023). Yet, the resulting inferences and recommendations should be considered with caution. Specifically, as shown by Lee et al. (2022), low levels of AI adoption were not associated with significant revenue growth; rather, revenue growth emerged only as the intensity of AI adoption increased and firms made sufficient AI investments. These insights help us add some context to our findings: specifically, though not included in our empirical findings, the lack in clear productivity gains may be due to a lack of investment amongst SMEs which in turn may be required

to reap labour productivity gains. Our dependent variable here only allows us to consider whether – or not – a firm actually adopted AET, meaning that we have no information on AET intensity and AET investments made by firms. Thus, further research is needed to tease out the intricacies associated with the seemingly complex relationship between AET adoption and productivity implications. Again, while the findings presented here should be considered in view of the aforementioned data limitations, one key recommendation arising for policy makers is to purposefully fund relevant future research based on UK data. Additionally, given that using external information/advice is persistently linked to productivity (based on our empirical results), policy makers may consider how access to relevant knowledge sources may be facilitated, as this may have potential benefits for both labour productivity and AET adoption.

Overall Conclusion

This research highlights the important role of external information and advice in AET adoption among UK SMEs, with firms using such knowledge showing a higher likelihood of adoption. Importantly, both the reason and source of external information and advice appear to matter. While AET adoption alone does not show a robust association with labour productivity, the findings overall suggest that strengthening SMEs' access to relevant external knowledge, and ensuring that this support is aligned with firms' innovation and efficiency needs, may be an important part of supporting the wider diffusion of AET.

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Appendices

Appendix A: Correlations Table

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) AET	1.000														
(2) extknow	0.105	1.000													
	(0.000)														
(3) size	0.102	0.130	1.000												
	(0.000)	(0.000)													
(4) agecat	0.000	0.042	0.174	1.000											
	(0.988)	(0.000)	(0.000)												
(5) rd	0.194	0.183	0.169	0.022	1.000										
	(0.000)	(0.000)	(0.000)	(0.044)											
(6) Women	-0.044	-0.002	-0.053	-0.061	-0.076	1.000									
	(0.000)	(0.827)	(0.000)	(0.000)	(0.000)										
(7) Turnover	0.107	0.168	0.649	0.268	0.239	-0.143	1.000								
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)									
(8) ExpGrow	0.039	0.094	0.116	-0.111	0.144	0.012	0.098	1.000							
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.299)	(0.000)								
(9) ExpShrink	-0.007	0.009	-0.060	0.044	-0.032	0.007	-0.058	-0.331	1.000						
	(0.543)	(0.407)	(0.000)	(0.000)	(0.004)	(0.520)	(0.000)	(0.000)							
(10) Family	-0.014	-0.099	-0.220	-0.104	-0.056	0.069	-0.249	-0.009	0.031	1.000					
	(0.186)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.420)	(0.006)						
(11) Ethnic	0.027	0.011	0.105	-0.047	0.020	0.008	0.051	0.019	-0.019	-0.093	1.000				
	(0.014)	(0.334)	(0.000)	(0.000)	(0.073)	(0.465)	(0.000)	(0.096)	(0.105)	(0.000)					
(12) Exporting	0.122	0.089	0.099	0.094	0.295	-0.090	0.255	0.084	0.014	-0.063	0.000	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.191)	(0.000)	(0.985)				
(13) SECTOR	-0.003	0.042	-0.041	-0.063	-0.069	0.169	-0.221	-0.011	0.010	-0.187	0.103	-0.136	1.000		
	(0.807)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.317)	(0.342)	(0.000)	(0.000)	(0.000)			
(14) rural	-0.014	-0.011	-0.071	0.014	-0.024	-0.021	-0.067	-0.008	-0.031	0.126	-0.112	-0.043	-0.126	1.000	
	(0.199)	(0.297)	(0.000)	(0.209)	(0.027)	(0.055)	(0.000)	(0.453)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)		
(15) legal	-0.019	0.058	0.114	0.120	-0.032	-0.032	0.128	-0.030	-0.015	-0.282	0.059	-0.031	0.085	-0.022	1.000
	(0.078)	(0.000)	(0.000)	(0.000)	(0.003)	(0.004)	(0.000)	(0.007)	(0.173)	(0.000)	(0.000)	(0.004)	(0.000)	(0.040)	

Appendix B: Variance Inflation Factors

	VIF	1/VIF
extknow	1.073	.932
lsize	3.504	.285
agecat	1.175	.851
2.SECTOR	1.69	.592
3.SECTOR	1.809	.553
4.SECTOR	1.547	.646
2.Turnover	1.854	.539
3.Turnover	1.874	.534
4.Turnover	2.343	.427
5.Turnover	2.672	.374
6.Turnover	3.053	.328
7.Turnover	2.684	.373
8.Turnover	1.905	.525
9.Turnover	1.726	.579
10.Turnover	1.673	.598
Women	1.073	.932
Ethnic	1.044	.958
Family	1.186	.843
rural	1.053	.949
ExpGrow	1.2	.833
ExpShrink	1.151	.869
2.legal	2.321	.431
3.legal	1.833	.545
4.legal	1.268	.789
rd	1.235	.81
Exporting	1.205	.83
2019.surveyyear	1.21	.826
2020.surveyyear	1.19	.84
2021.surveyyear	1.243	.804
Mean VIF	**1.683**	.

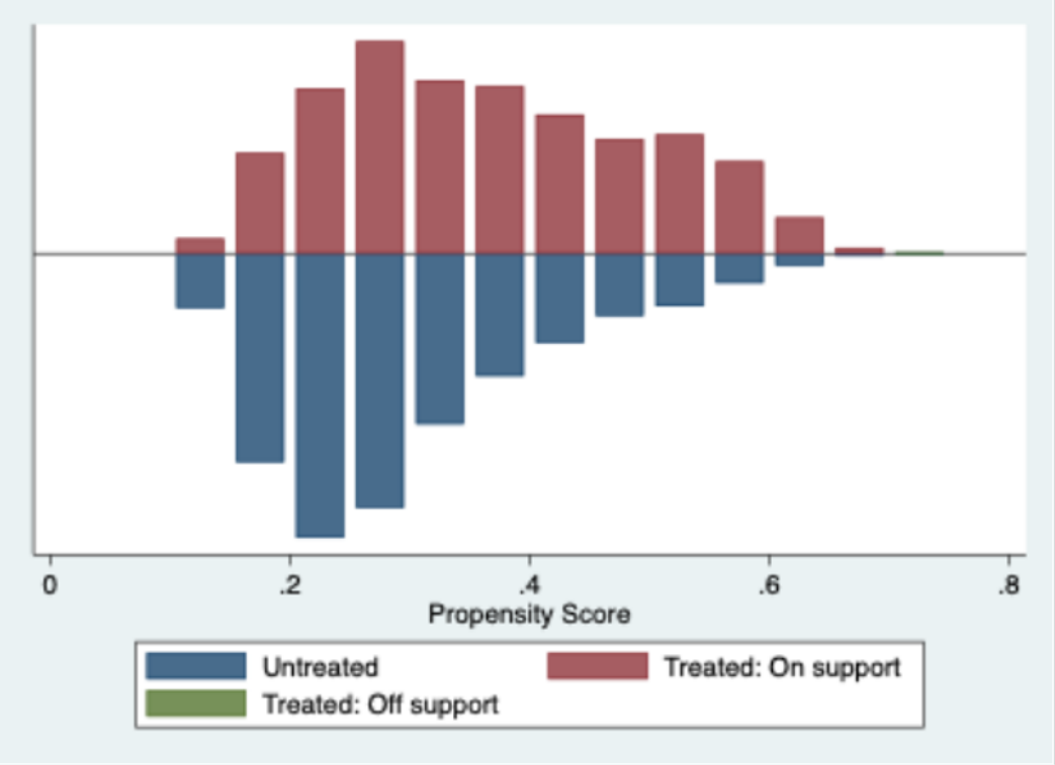
Appendix C: Propensity Score Matching Procedure

Table C1: Propensity score model

	Coefficient	*t*
Firm size (log)	0.103**	(2.94)
Firm age (bands)	0.00974	(0.33)
Sector		
ABCDEF – Production and construction	base	
GHI – Transport, retail and food service/accommodation	-0.0303	(-0.37)
JKLMN – Business services	0.303***	(3.92)
PQRS – Other services	0.413***	(3.79)
Turnover (bands)	0.0755***	(3.46)
Women-led	0.167*	(2.13)
Ethnic minority-led	-0.132	(-1.23)
Family-owned	-0.0481	(-0.70)
Rural location	0.0991	(1.58)
Expects growth	0.324***	(5.29)
Expects contraction	0.328***	(3.35)
Legal form		
Sole proprietorship	base	
Company	0.196	(1.79)
Partnership	0.331*	(2.35)
Other	0.371	(1.70)
Conducts R&D	0.686***	(10.59)
Exporting	0.0672	(1.01)
Survey year		
2018	base	
2019	-0.0196	(-0.26)
2020	-0.0584	(-0.69)
2021	0.0425	(0.57)
Constant	-2.112***	(-12.42)
Observations	6,378	

Notes: Dependent variable is external knowledge and advice seeking. t statistics in parentheses. Base denotes the omitted reference category. * p<0.05, ** p<0.01, *** p<0.001.

Figure C1: Treated and control groups distribution



Appendix C Table C2: Covariate balance table

Covariate balance table								
	Unmatched	Mean			%reduct	t-test		V(T)/
Variable	Matched	Treated	Control	%bias	bias	t	p>t	V(C)
Size(logs)	U	2.5757	2.0661	35.7		13.32	0	1.03
	M	2.5742	2.5347	2.8	92.2	0.87	0.382	0.99
Age(cat)	U	3.1011	3.0117	8.6		3.21	0.001	0.97
	M	3.1007	3.0918	0.9	90.1	0.28	0.783	1.02
Sector								
GHI - Transport, retail and food service/ accommodation	U	0.2484	0.30131	-11.9		-4.37	0	.
	M	0.24853	0.24705	0.3	97.2	0.11	0.913	.
JKLMN - Business services	U	0.40108	0.36259	7.9		2.96	0.003	.
	M	0.40079	0.40668	-1.2	84.7	-0.38	0.702	.
PQRS - Other services	U	0.12077	0.10712	4.3		1.61	0.106	.
	M	0.12083	0.11788	0.9	78.4	0.29	0.772	.
Turnover(cat)	U	4.4737	3.6404	35.7		13.45	0	1.14*
	M	4.471	4.4072	2.7	92.3	0.85	0.396	1.02
Women	U	0.162	0.1578	1.1		0.43	0.669	.
	M	0.16159	0.15521	1.7	-51.8	0.56	0.577	.
Ethnic	U	0.07658	0.07302	1.4		0.51	0.613	.
	M	0.07662	0.07711	-0.2	86.2	-0.06	0.953	.
Family	U	0.71232	0.78185	-16		-6.07	0	.
	M	0.71267	0.72151	-2	87.3	-0.63	0.531	.
Rural	U	0.29259	0.30062	-1.8		-0.65	0.513	.
	M	0.29224	0.28536	1.5	14.4	0.48	0.628	.
ExpGrow	U	0.56259	0.46049	20.5		7.64	0	.
	M	0.56238	0.55501	1.5	92.8	0.47	0.636	.
ExpShrink	U	0.10506	0.10343	0.5		0.2	0.843	.
	M	0.10511	0.10609	-0.3	39.5	-0.1	0.919	.
Legal form								
Company	U	0.82572	0.76319	15.5		5.66	0	.
	M	0.82564	0.84234	-4.1	73.3	-1.43	0.152	.
Partnership	U	0.08051	0.08569	-1.9		-0.7	0.487	.
	M	0.08055	0.06876	4.3	-127.4	1.43	0.153	.
Other	U	0.02307	0.01912	2.8		1.04	0.298	.
	M	0.02308	0.02407	-0.7	75.2	-0.21	0.836	.
R&D	U	0.40255	0.217	41		15.75	0	.
	M	0.40226	0.39244	2.2	94.7	0.64	0.522	.

Exporting	U	0.33235	0.24925	18.4		6.95	0	.
	M	0.33202	0.32711	1.1	94.1	0.33	0.739	.
2019	U	0.216	0.20663	2.3		0.86	0.391	.
	M	0.21611	0.21611	0	100	0	1	.
2020	U	0.15071	0.16079	-2.8		-1.03	0.303	.
	M	0.15079	0.14735	0.9	65.9	0.31	0.758	.
2021	U	0.22975	0.21631	3.2		1.21	0.228	.
	M	0.22986	0.23183	-0.5	85.4	-0.15	0.882	.
** If variance ratio outside [0.92; 1.09] for U and [0.92; 1.09] for M*								

Appendix C Table C3: Average treatment effect of the treated (ATT)

Variable	Sample	Treated	Controls	Difference	S.E.	T stat
AET	Unmatched	0.117329406	0.05666897	0.060660436	0.007079266	8.57
	ATT	0.117387033	0.074656189	0.042730845	0.009211945	4.64
		Seekers	Non seekers			
Note: S.E. does not take into account that the propensity score is estimated.						

Appendix D: Full margins output for Table 6

Margins output for Model 2:

Model 2					
margins,	dydx(extknow)				
Average marginal effects	Number of obs=	6,378			
Model	VCE:	Robust			
Delta-method					
dy/dx	std. err	z	P>|z|	[95%	conf. interval]
0.028792	0.006743	4.27	0	0.0155757	0.0420084

Margins output for Model 3:

Model 3						
margins,	dydx(extknow)					
Average marginal effects	marginal	effects Number	of	obs	=	4,072
Model	VCE:	Robust				
Delta-method						
dy/dx	std. err	z	P>|z|	[95%	conf. interval]	
0.0395339	0.00915	4.32	0	0.0216	0.05747	

Appendix E: Robustness checks

Appendix E Table E1: AI and VR/AR as separate dependent variables

	Model A	Model B
	AI	VR/AR
External information/advice	**0.434*** **	**0.463** **
	(0.116)	**(0.176)**
Firm characteristics		
Size (log)	0.056	-0.035
	(0.076)	(0.115)
Age (bands)	**-0.155***	**0.005**
	(0.063)	(0.094)
Conducts R&D	0.999***	0.849***
	(0.136)	(0.199)
Turnover		
Turnover=2	0.087	0.527
	(0.211)	(0.323)
Turnover=3	-0.260	0.443
	(0.275)	(0.425)
Turnover=4	-0.165	-0.015
	(0.288)	(0.446)
Turnover=5	-0.025	0.353
	(0.286)	(0.411)
Turnover=6	0.129	0.806
	(0.303)	(0.454)
Turnover=7	0.516	0.720
	(0.329)	(0.491)
Turnover=8	0.327	1.031
	(0.398)	(0.575)
Turnover=9	0.667	1.377*
	(0.426)	(0.589)
Turnover=10	0.751	1.251*
	(0.441)	(0.622)
Women-led	-0.426*	0.277
	(0.197)	(0.261)
Family-owned	0.187	-0.084
	(0.137)	(0.206)

Ethnic minority-led	0.271	0.513*
	(0.194)	(0.252)
Company	0.211	-0.218
	(0.270)	(0.375)
Partnership	0.310	-1.071
	(0.347)	(0.628)
Other	0.352	-0.838
	(0.475)	(0.767)
Exporting	0.426***	0.542**
	(0.128)	(0.198)
Expects growth	-0.036	0.178
	(0.126)	(0.191)
Expects shrink	0.101	0.215
	(0.195)	(0.300)
Rural location	0.035	-0.090
	(0.133)	(0.226)
GHI - Transport	-0.705***	-.0361
	(0.189)	(0.312)
JKLMN - Business services	0.339*	0.844**
	(0.147)	(0.257)
PQRS - Other services	-0.318	0.165
	(0.259)	(0.467)
2019	0.633***	0.656**
	(0.143)	(0.223)
2020	0.371*	0.650**
	(0.170)	(0.246)
2021	0.747***	0.770***
	(0.146)	(0.227)
Constant	-3.967***	-5.599***
	(0.386)	(0.620)
Observations	6378.000	6378
Log likelihood	-1265.982	-638.581
Wald chi2	291.695	170.300

Appendix E Table E2: Probit specification

	Probit
External information/advice	**0.228*** (0.053)**
Firm characteristics	
Size(log)	0.030 (0.034)
Age (bands)	-0.055* (0.028)
Conducts R&D	0.499*** (0.058)
Turnover:	
Turnover=2	0.049 (0.092)
Turnover=3	-0.074 (0.120)
Turnover=4	-0.038 (0.127)
Turnover=5	0.017 (0.127)
Turnover=6	0.165 (0.137)
Turnover=7	0.251 (0.151)
Turnover=8	0.204 (0.188)
Turnover=9	0.478* (0.197)
Turnover=10	0.539** (0.207)
Women-led	-0.082 (0.080)
Family-owned	0.065 (0.063)

Ethnic minority-led	0.194*
	(0.086)
Company	-0.018
	(0.106)
Partnership	-0.058
	(0.146)
Other	-0.096
	(0.204)
Exporting	0.238***
	(0.059)
Expects growth	-0.022
	(0.056)
Expects shrink	0.004
	(0.088)
Rural location	0.006
	(0.061)
Sector	
GHI – Transport, retail and food services	-0.270***
	(0.082)
JKLMN - Business services	0.256***
	(0.070)
PQRS - Other services	-0.073
	(0.114)
Survey year	
2019	0.316***
	(0.064)
2020	0.209**
	(0.074)
2021	0.381***
	(0.065)
Constant	-2.054***
	(0.163)
Observations	6378
Log likelihood	-1505.232
Wald chi2	356.604

Appendix E Table E3: SME sub-sample (<250 employees)

	AET
External information/advice	**0.452*** (0.104)**
Firm characteristics	
Size(log)	0.059 (0.069)
Age (bands)	-0.118* (0.056)
Conducts R&D	0.975*** (0.119)
Turnover:	
Turnover=2	0.114 (0.188)
Turnover=3	-0.167 (0.251)
Turnover=4	-0.137 (0.257)
Turnover=5	0.024 (0.254)
Turnover=6	0.292 (0.273)
Turnover=7	0.492 (0.294)
Turnover=8	0.348 (0.365)
Turnover=9	0.862* (0.377)
Turnover=10	0.972* (0.391)
Women-led	-0.177 (0.165)
Family-owned	0.128 (0.124)
Ethnic minority-led	0.376*

	(0.166)
Company	-0.019 (0.225)
Partnership	-0.111 (0.314)
Other	-0.105 (0.420)
Exporting	0.481*** (0.116)
Expects growth	-0.033 (0.112)
Expects shrink	0.034 (0.177)
Rural location	-0.015 (0.123)
Sector	
GHI – Transport, retail and food services	-0.585*** (0.171)
JKLMN - Business services	0.499*** (0.138)
PQRS - Other services	-0.146 (0.236)
Survey year	
2019	0.620*** (0.128)
2020	0.422** (0.150)
2021	0.744*** (0.130)
Constant	-3.737*** (0.339)
Observations	6374
Log likelihood	-1503.530
Wald chi2	369.455

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