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Lessons from the implementation and evaluation of the Greater London Authority "Grow with AI" programme

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ABSTRACT

The “Grow with AI” programme was a randomised controlled trial that sought to test barriers to adoption of “tried-and-tested” Artificial Intelligence (AI) technologies in London’s retail and hospitality sectors. Light-touch market-convening events were compared with more targeted caseworker support and a voucher, and with a control group that received only written information. Due to recruitment and implementation challenges, the trial did not obtain a large enough sample to enable robust econometric evaluation. However, adoption-related activity was observed to be higher in the two treatment groups than in the control group. Firms in all groups reported having a better understanding of the costs and benefits by the end of the trial, but attitudes towards AI worsened. The difficulties with recruitment and take-up suggest that the support offered in this trial did not meet the priorities of the businesses targeted. Interviews with a sample of participants highlighted that the AI technologies being promoted were not as “shovel-ready” as had been expected. However, interview responses also suggest that SMEs understand the importance of technological upgrading, and are willing to adopt new tools as long as they prove to be cost-effective.

Keywords: SMEs, technology adoption, artificial intelligence

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Lessons from the implementation and evaluation of the Greater London Authority "Grow with AI" programme[1]

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[1] The study protocol and Pre-Analysis Plan were filed at the AEA Registry (see Valero, 2019). This work contains statistical data from the ONS, which is Crown Copyright. The use of ONS statistical data does not imply the endorsement of the ONS in relation to the interpretation or analysis of the data. This work uses research datasets, which may not exactly reproduce National Statistics aggregates.

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Executive summary

Background

- This report describes the findings of our evaluation of the “Grow with AI” programme, a randomised control trial that has sought to understand the barriers to adoption of “tried-and-tested” Artificial Intelligence (AI) technologies in London’s retail and hospitality sectors, and how these can be addressed.
- This trial was designed and implemented in a collaboration between the Greater London Authority (GLA), CognitionX, Capital Enterprise, and it was funded by the BEIS Business Basics Programme (BBP). Businesses were recruited into the study over three waves during 2019 and 2020, and the interventions took place in 2020.
- This trial tests the effectiveness of two types of intervention: light-touch market-convening events (T1) and more targeted caseworker support and a voucher (T2), versus a control group, for encouraging SMEs to adopt chatbots and marketing automation technologies, and for stimulating innovation and productivity improvements more broadly.
- Due to recruitment and implementation challenges both pre and post the pandemic, we have not achieved a large enough sample to enable robust econometric evaluation. However, we combine quantitative insights from our baseline and endline surveys, together with qualitative insights from interviews with participating firms, in order to provide findings that are relevant for the design of future business support programmes and future research projects on technology adoption and on the retail and hospitality (and related) sectors.

Key findings

- While we are unable to generate robust estimates of treatment effects in this study, it appears that adoption-related activity (in particular allocating resource towards exploring the adoption of AI technologies) in the treatment groups was higher than in the control group – though there was no discernible difference in terms of actual adoption of chatbots and marketing automation.
- Firms in all groups reported having a better understanding of the costs and benefits at endline, but attitudes towards AI worsened (in the treatment groups this appears to be driven by non-participating firms).
- Our data have helped to shed light on the barriers to AI adoption faced by retail and hospitality SMEs, showing that, in line with other surveys on broader technologies and with wider sectoral/geographic coverage, the top three ranked barriers relate to financing constraints (the costs of new software and reorganisation) and skills. Information and time barriers were also emphatically underlined during the interviews. As we intended in the programme design, we found quantitative and qualitative evidence that firms in the T2 group, who received a more targeted intervention, considered that the programme addressed barriers to a greater extent than firms in T1.
- All firms that answered the endline survey had sought external advice on technology in addition to the programme - mainly relating to non-AI technologies and likely driven by the fact that a large share of respondents had reassessed their technology needs, or adopted new technologies, in response to the Covid-19 crisis.

- Qualitative interviews highlighted that the AI technologies in scope were perhaps not as “shovel-ready” as anticipated, with an emphasis on technology inaccuracy rates and the continued need for human input in such cases. Consultants providing support to SMEs might not be able to precisely forecast the time and resources that firms would need to transition to these technologies as these will be influenced by firm and technology specific factors.

Policy implications

- At a high level, we can conclude that the trouble we had recruiting participants and the low take-up suggests that the support offered by this programme, and the way in which it was delivered, did not address the priorities of our sample of businesses pre- or post-pandemic.
- However, those that responded to the endline survey reported that the trial addressed many barriers to technology adoption, and improved their understanding of these technologies.
- We have found evidence that firms in these sectors are interested in technology adoption and in receiving technology advice. Indeed, all firms in our endline sample had sought external advice on technology adoption, though much of this appears to have been prompted by the pandemic.
- Our qualitative evidence also suggests that SMEs understand the importance of technological upgrading to their business performance and the UK economy more broadly, and seem willing to adopt these tools as long as they prove to be cost-effective. Interviewees appreciated the government’s effort to provide business support on technology adoption, and hoped that this would continue in the future.
- This programme helped inform the design of a new searchable online platform and marketplace of technology providers for small businesses on the London Business Hub, launched in March 2021.

Lessons for future trials

- A key lesson we have learned is that future programmes of business support targeted at small businesses in retail and hospitality (or similar) sectors, and associated trial designs, should take active steps to anticipate that managers have limited time, and are likely to struggle to attend “in-person” interventions. More flexibility in the provision of support, including remote provision, is likely to be beneficial for this target audience.
- Future trials focused on SMEs should ensure that the information provided is sector-specific, and draw attention to the practical, day-to-day challenges of the technology adoption journey. Furthermore, technologies on offer should not only be “tried-and-tested”, but also “shovel-ready” and customisable for that target demographic.
- The most successful method of recruitment, direct phone marketing, was resource-intensive, and also led to the recruitment of businesses that did not necessarily have an effective understanding of the programme offer. Moreover, there were issues with respect to the quality of contact information. It might be preferrable to confirm contact details upon acceptance into the programme, and build more flexibility and automation into the interventions themselves.

1. Introduction

This report describes the findings of our evaluation of the "Grow with AI" programme, a randomised control trial that has sought to understand the barriers to adoption of "tried-and-tested" AI technologies in London's retail and hospitality sectors, and how these can be addressed. This trial was designed and implemented in a collaboration between the Greater London Authority (GLA), CognitionX, Capital Enterprise and it was funded by the BEIS Business Basics Programme (BBP). The BBP was announced in the government's Industrial Strategy in 2017, and was designed to test innovative ways of encouraging small and medium-sized enterprises (SMEs) to adopt existing technologies and management practices to improve their productivity. A key aim of the programme is to add to the evidence base of what works in terms of improving the productivity performance of SMEs. The BBP is delivered on behalf of BEIS through a partnership with Innovate UK and the Innovation Growth Lab at Nesta.

Motivation for the "Grow with AI" programme

Poor productivity performance in the UK since the global financial crisis has widened the pre-existing productivity "gap" with its core comparator countries, and has prompted numerous government-led initiatives to understand and address the "productivity puzzle", including the BBP. Some elements of the UK's puzzle have been part of a wider international phenomenon: productivity growth has slowed across advanced economies since 2008. It is widely accepted that the driver of the international productivity puzzle is a slowdown in total factor productivity (TFP) growth – i.e. slowdowns in measured output growth are not accounted for by slowdowns in measured input growth (OECD, 2015). "Technology optimists" consider that once emerging technologies, such as artificial intelligence (AI), diffuse through the economy, a new wave of productivity growth will occur (Brynjolfsson et al, 2018). This view relies on complementary factors, including skills and managerial practices, becoming more widespread. Others are more pessimistic, arguing that new technologies have less productivity impact than those that preceded them (for example, Cowen, 2011; Gordon, 2018). Shedding light on the firm-level impacts of adopting such emerging technologies is therefore important for informing this debate. However, there are also UK-specific elements to the puzzle. The country's poor productivity performance has been particularly pronounced and prolonged by international standards, and this was the case even before the UK entered a period of uncertainty following the EU referendum in 2016 and the Covid-19 crisis in 2020.

A particular issue holding back UK productivity growth has been the "long tail" of unproductive and generally smaller firms. These firms also tend to underinvest in modern technologies or management practices. According to the World Economic Forum's World Competitiveness Report (2019), "ICT [Information and Communications Technology] adoption, while increasing, remains low by OECD standards: the country ranks 31st globally and only 16th in Europe". Similarly, the European Commission's Digital Scoreboard shows that digital intensity among UK enterprises is middling relative to EU countries.[2]

The focus of this study is on the adoption of "tried-and-tested" AI technologies in London's retail and hospitality SMEs. Research have estimated that AI in general has the potential to raise productivity in the UK by up to 30% in some sectors by 2024 (Hall and Pesenti, 2017). But AI is a multi-faceted technology group, and, in this project, we focus on AI deployments which are relevant for retail and hospitality SMEs: chatbots and marketing automation tools.

[2] See Figure 3 in Martin et al., (2020) which is based on these data.

Chatbots enable companies to provide on-demand customer assistance, including for making reservations (hospitality), answering customer queries, or making recommendations. Marketing automation tools provide companies with the ability to build a better understanding of their customers and tailor marketing content to the individual customer and location across multiples channels.[3] These technologies can help to convert enquiries and leads into sales and have the potential to augment the value of existing jobs and employees, rather than replace the need for certain jobs or members of staff. Moreover, their cost – typically incurred on a subscription basis – tends to be within the spending profile of SMEs in retail and hospitality.

Retail and hospitality are considered to be "low-wage" (or "low-productivity") sectors (see, for example, Thompson et al., 2016). They tend to account for a high share of employment in London and across the country, implying that raising productivity via improving the adoption of productivity-enhancing technologies and practices in such sectors could have a large impact in aggregate (Bernick et al., 2017). Indeed, the UK Innovation Survey has consistently shown that the share of businesses introducing "process innovation"[4] in retail and hospitality sectors has been relatively low. In the latest data for 2016-18, 12.7% of businesses were process innovators across sectors, but the equivalent figures for "Retail Trade" and "Accommodation and Food Services" were 8.5% and 5.6%, respectively (UK Innovation Survey, 2019).

Relevance in light of the pandemic

While this study was designed before the pandemic (the study protocol was filed in 2019), understanding the drivers of technology adoption in retail and hospitality businesses is of particular interest, given that these sectors have been hit hard due to lockdowns, social distancing requirements, and changing patterns in consumption, work and commuting, especially in London. Survey evidence to date suggests that many firms have had to adapt their business models, including via the use of technology. In a survey carried out with the CBI a few months into the pandemic, Riom and Valero (2020) found that Covid-19 had accelerated the adoption of digital technologies, and that adoption was more likely in London businesses, and in businesses that had previously adopted new digital technologies in the recent past.[5]

Part of the implementation of this programme, and all the endline surveys, have taken place during the Covid-19 crisis. We have updated our approach as necessary in order to remain relevant for participants and generate findings that apply in this new context. While the pandemic may have changed business priorities, it is clear that technology (broadly defined) has played an important role during it, and will continue to do so in the economic recovery. The need for building a deeper understanding on the barriers to adoption in firms, evaluating technology support policies, and adjusting them in light of evolving evidence is therefore as crucial as ever.

Objectives

The key aim of this trial is to add to the evidence base on what works in terms of encouraging technology adoption in SMEs. Specifically, this trial seeks to understand what type of

[3] For more details of relevant examples, see the "Guide to AI for SMEs in Retail and Hospitality" (Appendix 9) which was prepared by CognitionX and shared with all project participants, including the control group (as discussed in Section 2.1).
[4] This is defined as introducing "significant changes in the way that goods or services are produced or provided, […] differentiating between processes new to the business only or also new to the industry."
[5] See Valero and Van Reenen (2021) for broader discussion on how Covid-19 has, and may be expected to, affect firms' adoption of new technologies and business practices.

intervention (light-touch versus more targeted) works for encouraging SMEs to adopt cutting-edge, but tried-and-tested, AI technologies, and stimulating innovation and productivity improvements more broadly. To do this, we have sought to test two methods of catalysing the adoption of chatbots and marketing automation technology. Treatment 1 is a market convening methodology based on the idea that information about the technologies and contact with the vendors are sufficient to increase adoption of AI tools amongst SMEs. Treatment 2 is a more targeted intervention based on the idea that access to independent, tailored advice and some financial support is needed in order to increase uptake of AI amongst SMEs.

While increasing focus on the evaluation of business support programmes and incentives in recent years has begun to shed light on what works, high-quality evidence is still scarce, particularly in high-income countries, such as the United Kingdom. A literature review by the What Works Centre for Local Economic Growth (WWC) in 2016 found that only 23 of over 700 studies on business advice were robust.[6] Moreover, previous experiments to encourage UK firms to adopt productivity-enhancing practices have been met with limited success (Bakhsi et al., 2013 on creative credits; BIS., 2014 on growth vouchers; and Breinlich et al., 2017 on export promotion). In a BBP-funded trial, Roper et al., (2020) find evidence of positive impacts of business support workshops on awareness of growth/performance-related tools amongst young microbusinesses, and some increase in the use of these tools in the short run.

Much of the evaluation literature has tended to focus on the longer-term determinants of innovative activities in firms, often measured using Research & Development (R&D) or Intellectual Property (IP) indicators. A larger gap, however, exists in what is known about the adoption or diffusion of innovation in firms (Bravo-Biosca and Stouffs, 2018). There is therefore a need to build more evidence on the causal effects of policies that seek to stimulate the adoption of new technologies and their impacts on business performance, and this has prompted a number of government initiatives, including the BEIS Business Basics Programme.

Our initial hypothesis was that underinvestment in productivity-enhancing AI technologies by SMEs is driven by a combination of barriers, including lack of information and motivation (internal capacity), financial constraints, and risk aversion. Our two interventions (light-touch versus more targeted) were designed to address these to differing degrees. Moreover, our study design is innovative in three ways. First, it tests two methods that seek to lower barriers for SME AI technology adoption based on the views and practices of AI experts and business-support practitioners. Second, it focuses on emerging technologies (chatbots and marketing automation), which are nevertheless "tried-and-tested" and where potential productivity gains are thought to be high. Third, its focus is on the retail and hospitality sectors, which are not traditionally the target of business support initiatives, despite being large employers in London and across the UK.[7]

Our key objective is to contribute to the literature on the evaluation of business support policies that relate to technology adoption. Due to recruitment and implementation challenges both pre- and post-Covid, we have not achieved a large enough sample to enable robust econometric evaluation. However, we combine quantitative insights from our baseline and endline surveys, together with qualitative insights from interviews with participating firms, in order to provide

[6] Impact evaluations considered as robust were those that scored 3 or higher in the Maryland Scientific Methods Scale (SMS). The SMS is a five-point scale ranging from 1, for evaluations based on simple cross-sectional correlations, to 5 for randomised controlled trials (WWC, 2016).
[7] See WWC (2016) on sector targeting. Most programmes are not restricted by firm sector.

findings that are relevant for the design of future business support programmes and future research projects.

While the setting for this study is London and a key objective was to inform GLA business technology support policies, we seek to inform the UK Government more broadly with respect to the most effective policies for improving the uptake of technologies or innovative practices amongst SMEs. This has been a key area of focus in the government's "Industrial Strategy" (2017 White Paper) and current "Plan for Growth" (which accompanied Budget 2021). Similarly, we expect our findings to be relevant for other regions and countries; and indeed, other sectors with business models that are similar to retail and hospitality (e.g. entertainment, sport, tourism, music, and theatre). More broadly, our findings will also have implications for policies that seek to grow the AI sector via shedding light on how to increase diffusion and, hence, demand for new technologies.

Overview of this report

This report is structured as follows. Section 2 sets out our methodology, describing in detail the design of the programme, setting out how initial plans were adapted in light of a series of challenges faced in recruitment and participation. Section 3 describes the data from our baseline survey. Section 4 describes and analyses key outcomes and project monitoring data using the endline survey, findings from our qualitative interviews, and inspection of firm websites. Section 5 draws out relevant lessons for policy and future research and concludes.

2. Trial methodology and design

2.1. The intervention

This study was designed and implemented in a collaboration between the Greater London Authority (GLA), CognitionX, Capital Enterprise, with the LSE team as evaluation partners. The design of the randomised control trial, as set out in our study protocol, was developed by members of the team in partnership with members of the BEIS Business Basics Programme team and the Innovation Growth Lab at NESTA. The programme was initially called "AI for SMEs"[8], but was branded as "Grow with AI" in business-facing communications by the Greater London Authority and implementation partners.

Our objective was to test two methods of catalysing the adoption of chatbots and marketing automation technology amongst SMEs in London's retail and hospitality sectors. Treatment 1 (T1) is a "light-touch" market-convening methodology and Treatment 2 (T2) is a more tailored approach, with access to independent expertise and financial incentives to trial the new technology. This experiment therefore tests the intensity of the support which is necessary to increase adoption of a poorly understood technologies, which, in turn, will shed light on the cost-effectiveness of these two different approaches.

Due to difficulties in recruiting businesses and, subsequently, following disruptions due to Covid-19 (discussed in more detail below), the delivery of the interventions and our approach to the evaluation have evolved over time. In terms of implementation, we decided to adopt a cohort model, so that three cohorts would be sequentially recruited, and interventions delivered

[8] This is the project name in terms of project documentation and AEA Registry documents (Protocol and Pre-Analysis Plan), see https://www.socialscienceregistry.org/trials/3999.

for each cohort in turn. This approach was taken in order to avoid excessive delay and hence risk losing companies that signed up early in the process.

Treatment 1

This treatment arm was delivered by CognitionX[9] (CX), an expert AI platform which regularly runs events that bring together buyers and AI vendors, including an annual festival of AI. It was motivated by their previous experience of business adoption of AI, and an interest amongst businesses in events showcasing customer case studies and vendor presentations. In this treatment, we sought to create such events, and tailor them specifically for small businesses in the retail and hospitality sectors, which CX had not done previously. The events consisted of an introductory presentation from an AI expert at CX, discussing the application of chatbots and marketing automation in retail and hospitality, and a presentation from a vendor of a relevant technology to provide a real-life example. There were opportunities at these events for SME representatives to ask questions and interact. The first two events were in-person, and the last was delivered online due to the lockdown restrictions in place at the time. In testing this type of treatment versus a control group, we planned to test whether information and risk-aversion barriers appear to be key constraints to technology adoption, and whether bringing customers and vendors together would be sufficient to address them.

Treatment 2

This treatment arm was led by Capital Enterprise[10] (CE), a not-for-profit agency that supports, incubates, and invests in AI-first start-ups. CE deployed an applied AI caseworker who worked with randomly assigned SMEs in order to advise and support them to choose the most appropriate chatbot or marketing automation AI product, and then to support the deployment of the technology within their firms. The case worker acted as an independent technical adviser, helping SMEs to understand how chatbots and marketing automation technologies could be applied in their businesses, and to calculate the potential return on investment.

The events began with a general introduction to AI technologies and applicability in these sectors (as in T1), but then went into some depth about how businesses can think about their technology needs as part of their business plan. Participants were given some “homework” to prepare before their one-to-one meeting with the case worker. After meetings, firms could continue to contact the case worker via e-mail. Finally, SMEs were offered a £750 voucher, which they could claim after the purchase of technologies considered to be within scope of the study (this amount typically represents a few months of subscription of the types of technology in scope of the study). The voucher had an expiry date (by the end of the trial)[11], which was communicated to the SMEs to help incentivise take-up. Therefore, this treatment sought to address information and risk aversion constraints to a larger extent by providing deeper and more tailored support for businesses, while also addressing the financing constraint by offering a voucher. As for T1, the first two events were held in person and the last one was held online.

All firms - Control group and Treatments 1 and 2

[9] https://app.cognitionx.com/directory/news/

[10] https://capitalenterprise.org/

[11] We discuss issues regarding the implementation of the voucher in Section 5.4. Given the extensions to the project timeline, the end-date for voucher use was not particularly clear for participants. The key constraint for the project team regarded the ability to claim costs against the project after the project end date.

We incentivised involvement in the project for all companies (in particular, the control group) by giving all who signed up access to an information pack titled “Guide to AI for SMEs” (see Appendix 9). This was provided as a link in a “welcome to the programme” e-mail, which was sent by GLA to participants after eligibility checks had been conducted. This document was prepared by CX and contained descriptions of AI, chatbots and marketing automation, as well as some case studies of UK companies in the retail and hospitality sectors that have adopted these technologies. Therefore, all participants in this programme got a basic intervention that is likely to have some impact on knowledge and awareness of the technologies, if they read it. By design, the information pack tried not to encourage implementation but, instead, provide some incentive for businesses to remain in the trial, helping to avoid attrition at the endline survey.

2.2. Barriers to be addressed by the trial

In Table 1, we break down the likely barriers faced by SMEs across areas relating to internal capacity, financing constraints and risk, and consider the extent to which each treatment might be expected to address them ex-ante (as set out in the study protocol). We expected the two treatment arms to lower a number of barriers to adoption, but T2 was expected to address additional barriers relating to finance, and in being more targeted, we expected information and risk barriers to be addressed to a larger extent in this stream. In our baseline survey, we asked firms to score the barriers and, at endline, we asked treatment firms to assess the extent to which the programme helped address them (see Figure 10 for results).

Table 1: Barriers Matrix

Matrix of potential barriers for AI adoption amongst SMEs					
#	Categories	Barriers	Control info guide	T1 info guide + vendor event	T2 info guide + caseworker + voucher
1	Internal capacity	Lack of information on chatbots/marketing automation applications and potential benefits/costs	◔	◑	◕
2	Internal capacity	Lack of information on technology providers	◔	◕	◕
3	Internal capacity	Lack of required management/workforce skill	○	○	◔
4	Internal capacity	Business specific doubts over applicability - i.e. whether sales/marketing tasks can be automated	◔	◑	◕
5	Internal capacity	Resistance to change from management	◔	◑	◕
6	Internal capacity	Resistance to change from employees	○	○	○
7	Finance and costs	Financing constraints (regarding investment - e.g. software costs)	○	○	◑
8	Finance and costs	Costs of reorganisation (training, reallocating tasks)	○	○	◑
9	External risk - tech market	Uncertainty in technology market - rapid change, potential for lock-in	◔	◑	◕
10	External risk - market	Uncertainty over impacts on customers and hence revenues (e.g. privacy concerns)	○	◔	◑
11	External risk - competitors	Uncertainty over relevance and demand amongst SMEs in sector	◔	◑	◕
12	External risk - macro	Uncertainty about macroeconomic outlook due to COVID-19 (or Brexit, other macroeconomic trends)	○	○	○

2.3. Logic model

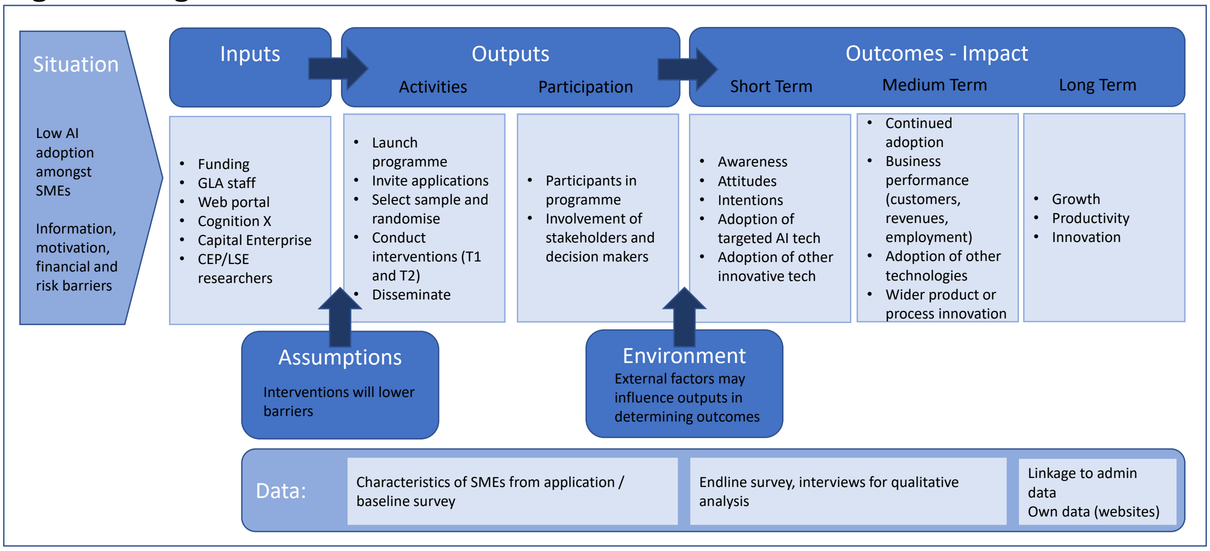
Figure 2 provides an outline of the logic model setting out the intended and anticipated impacts of the programme. The situation - as outlined in the introduction and discussion of barriers - is low productivity in the UK, and relatively low adoption of productivity-enhancing digital technologies, particularly within SMEs in "low-wage" sectors, such as retail and hospitality. Low adoption is the result of a series of barriers to adoption, which could include internal capacity, financial constraints and risk. The inputs in this programme include funding, the efforts and expertise of the team, and the production of a web portal hosted by the GLA for the "Grow with AI" programme, giving information and hosting the application process. The baseline survey was filled out by firms as they applied for the programme, and we made the assumption that the interventions we designed would address relevant barriers as set out above.

Broadly, the activities in this programme were designed in order to influence technology adoption, as well as a number of intermediate outcomes, which would measure how far firms are moving along the "adoption journey". These include changes in awareness, attitudes and intentions relating to the relevant AI technologies.

As we set out in the logic model, external factors also determine such outcomes, and the programme was conducted over a particularly difficult time for our target SMEs. Two large and unique macroeconomic shocks have occurred during this time: Brexit and Covid-19. These increased business uncertainty and are likely to have diverted SME attention from engaging in the programme and making new investments.

Baseline data were collected as part of the programme application process, and allowed us to check all applicants for eligibility. We collected monitoring data on the implementation process with our project partners in order to have information on participation status and interest in the programme. We collected endline survey data with the objective of being able to analyse key outcomes: business awareness, attitudes, intention, and actual adoption of AI (and other) technologies. We also inspected firms' websites in February 2021 in order to check whether chatbot technologies (which can be observed on a website) were present at that particular point in time.

Figure 1: Logic model



Sections 3.2 and 4 describe the participants in the study in more detail, and section 3.5 the precise outcomes as set out in the study protocol.

We expected participants to have some interest or awareness about the relevant AI technologies, since they had all signed up for the programme voluntarily. Our baseline data confirms that between 20 and 40% of our sample had taken various steps to inform themselves about these technologies before signing up to the programme (in this way, they might differ from the average London retail and hospitality SME). We therefore anticipated that participants would be at the "persuasion" stage of adoption (BEIS, 2019), i.e. the firms have been exposed to the existence of these chatbots and marketing automation technologies, are interested in them, and actively seeking information and details by participating in the programme. Within this stage, some SMEs might be further along in the process than others and, with our baseline questionnaire, we tried to measure the extent to which this is so.

We sought to test whether the interventions make it more likely that SMEs will take the decision to adopt the relevant technologies, or actually move to the implementation phase. Given the relatively short period between the interventions and evaluation,[12] we anticipated that potentially only a small shares might actually adopt the relevant AI technologies, and we were therefore unlikely to detect an effect on that outcome. For this reason, we also measured whether there had been any change in terms of decision-making and technology assessment processes.

Over the longer term, we set out plans to conduct follow-up surveys and carry out other data collection techniques to ascertain if the SMEs went into the confirmation stage – whereby they continue using the technology and might seek to optimise or expand that use, perhaps to broader innovation. While we collected information on self-reported performance in the survey (turnover or customers served), we had expected that the impacts on firm performance were more likely to be felt over the medium and long-term, particularly given the volatile economic environment over the study period. Linking data to secondary data sources (for example, the the Interdepartmental Business Register, IDBR) would allow us to track impacts on turnover, turnover per employee, employment or growth in such measures.

In our baseline survey, we also asked a series of questions that we anticipated might help explain any impacts detected. Namely, "overconfidence"[13] might be a behavioural barrier to investments in new technologies or practices, and it could also underlie a number of the barriers we set out (e.g. resistance to change from management; business specific doubts over applicability), though overconfidence might also be linked to a higher probability of management to take risks. Another potential behavioural barrier is a lack of growth ambition of management, i.e. those that are not driven by growing the business might be less interested in adopting new technologies.

Finally, we asked questions in our endline survey and in qualitative interviews to ascertain the extent to which participants found the interventions useful with respect to addressing the various barriers to adoption set out in Table 1. Such questions help to build understanding on the barriers to adoption, and can help explain some of the recruitment and implementation challenges faced by the programme.

2.4. Adapting our programme

In the initial stages of the programme, it became apparent that recruitment difficulties were the key threat to internal validity: without sufficient sample size, the study would be underpowered.

[12] The initial timeline set out in the study protocol was particularly short. This was extended in light of recruitment challenges and Covid-related disruptions.

[13] A survey of SMEs carried out by Be the Business found that that 79% of businesses believe that they are at least as productive as their peers (Be the Business, 2018).

This initial experience suggested that the assumptions made in the logic model about the willingness to come forward for support was overly optimistic. In response, we decided to pursue a more intense recruitment strategy involving direct approach over the phone, and progress the trial implementation in a cohort model with staggered and smaller events for those that we had recruited (to avoid excessive delay and potential drop-out). The vast majority of SMEs that signed up for the programme were contacted in this way, rather than via hearing about the programme from GLA or other business network communications[14] as initially envisaged. While firms recruited in this manner might be expected to be less motivated compared with firms that actively sought the programme out, there is still a degree of self-selection in our trial, which can harm external validity in terms of drawing conclusions for the average business.

We also faced problems in terms of lack of programme take-up and attrition at endline. We recruited 229 firms into the study, which were randomised across T1, T2 and the control group. In our Pre-Analysis Plan (PAP)[15], we highlighted concerns over a lack of power to detect impacts of the treatments relative to the control group. Given that only 43 SMEs completed the endline survey, we concluded that we have insufficient observations to conduct robust econometric analyses (we set out measures of compliance to treatment and endline survey in the next section). We therefore provide a descriptive analysis of our data in this report.

The macro-economic shocks of Brexit and the pandemic have impacted the implementation of the trial. Covid-19 has been particularly disruptive for businesses in London's retail and hospitality sectors – causing many businesses to shut down temporarily (or permanently) or to adopt other (non-AI) technologies in order to adapt their services (e.g. remote working or online sales). Before the shock, there was significant uncertainty over the UK's future trading relationship with the EU. Low take-up of the intervention and low participation in the endline survey casts some doubt on whether the programme was a priority for businesses that had initially signed up. However low take up is a common feature of randomised control trials offering business support in the UK. We explore the reasons for low take up and ask questions in our endline survey and in our qualitative interviews to understand the extent to which these shocks might have affected outcomes and whether our programme was useful for participants.

As a result of the recruitment difficulties we faced and Covid-related disruptions, we also extended the project timeline as compared with the initial plans. Moving towards a cohort model and a longer timescale meant that there was greater need to ensure consistency across interventions where they involved different people and delivery methods (in-person or online). In order to manage this, regular meetings were scheduled between the delivery team and the evaluation team to ensure that any changes in delivery between the cohorts were minimised. In T1, there was a smooth handover as a member of the team left after the Cohort 1 intervention, and while the CX presentations were not by the same individuals, we ensured consistency over the content and format. The CE interventions involved the same caseworker throughout, and he recruited and briefed another assistant to help with the one-to-one meetings.

[14] The GLA team coordinated outreach with a number of relevant organisations, including the Federation of Small Businesses (FSB) and a number of London's Business Improvement Districts (BIDs).
[15] https://doi.org/10.1257/rct.3999-4.0

3. Trial conduct

3.1. Timeline

The Grow with AI programme took place over 2019 and 2020, and key dates across the three cohorts are set out in Table 2. Baseline data were collected as part of the application process and, before proceeding to the survey, businesses were provided with information about the trial and asked a series of "consent" questions, in line with LSE research ethics requirements. All firms were recruited into the programme before the Covid-19 crisis, but Cohort 3's events were postponed and carried out in June 2020. We also delayed sending out endline surveys due to the crisis, and began this process for Cohort 1 in June-July 2020.

Due to delays in the implementation and in sending out endline surveys, the lag between interventions and follow-up surveys was shorter for the later cohorts as compared with the first.

Table 2: Date of recruitment and endline surveys

Cohort	Recruitment/baseline	Events	Mode	Endline
1	Apr-Aug 2019	T1, T2: 25th Sep 2019	In-person	Jun-Jul 2020
2	Sep-Dec 2019	T1, T2: 29th Jan 2020	In-person	Jul-Aug 2020
3	Jan-Feb 2020	T1: 30th Jun 2020 T2: 10th Jun 2020	Online	Nov-Dec 2020

In February/March 2021, we also contacted all firms that had participated in the endline survey and asked them if they would be willing to take part in an interview in order to provide feedback on their experience of the programme, and their broader views on technology in the current context. The four resulting interviews were conducted in March 2021.

3.2. Recruiting participants

The target group for this study was SMEs in London's retail and hospitality sectors. To be eligible, SMEs had to meet the following official criteria: employment count below or equal to 250, and turnover below £50 million. In addition, SMEs had to be registered in the UK, with headquarters or operations in London, and own a website or a Facebook page so that technologies in scope of the trial were relevant. We also required that SMEs had not already adopted the AI technologies in scope of study at the time of signing up to the programme. This was monitored through the baseline surveys and via the team inspecting the websites for evidence of chatbots at baseline (marketing automation would be harder to detect in this way). We found a small number of firms at baseline had basic messenger tools that required human interaction, but to the best of our knowledge, we found no evidence of AI-powered chatbots. Lastly, to reduce the risk of firms going out of business during the study period and follow up, SMEs also had to be more than 1 year old.

As mentioned, we adjusted our recruitment strategy during the course of the programme. The original recruitment target was 400 firms, with 100 firms in each treatment arm and 200 firms in the control group (see Trial Protocol). This target size was determined by a desire to have sufficient power to detect reasonable treatment effects within budget constraints (which were binding in the case of the need to budget for the provision of £750 vouchers to potentially all

T2 firms). The communications and outreach were led and coordinated by the GLA, who made use of the London Growth Hub, its policy and business networks (by e-mail and in person at London Growth Hub "Road shows"), and press and social media, to maximise SME applicants. However, it proved extremely challenging to recruit sufficient businesses using these methods alone and, in response to this, the team decided to re-design the outreach strategy. We employed three new methods. First, the GLA purchased a database with contact details for all eligible businesses, and sent GLA-headed e-mails to all firms. Second, we invested in targeted social media for subsectors within scope of the study led by the LSE. After we observed that these strategies were not yielding sufficient sign-ups, we contracted a market research company "Integral Research" (IR) to pilot a direct telephone campaign to recruit firms from samples of eligible businesses. IR was provided with a script (Appendix 3) to introduce participants to the trial and to direct participants to the GLA landing page, which included details of what was on offer in the different treatment streams, and more detailed trial information as part of the application process (see Appendix Figure 1 for an overview graphic that was provided on the project landing page). We found that the direct telephone campaign proved to be the most successful recruitment method and scaled this up for the other two cohorts. Details on the number of businesses contacted and number of calls made to each sign-up business, by cohort, are provided in Appendix 3. Overall, this is a labour-intensive, and therefore costly, method for recruiting businesses.

In order to understand how our sample compares to the average SME in their sectors, we compared their average revenue and employment to the averages from the IDBR. [16] The average monthly turnover of our sample of eligible SMEs when they signed up at baseline (in 2019-20) was £151,000 (s.d. £362,000), and they had on average 16 employees (s.d. 35). Firms that met the eligibility criteria that can be observed in the administrative data[17] had average turnover of £643,000 (s.d. £2.1m), and employment of 7.43 (s.d.16.5). Therefore, the firms in our sample appear to be, on average, smaller in revenue terms, and slightly larger in employment terms than the average of firms that were eligible for the programme. This suggests that the firms in our sample were, on average, lower productivity (where productivity is defined as turnover per employee) than the relevant population of SMEs in London.

3.3. Randomisation

For each cohort, once recruitment was closed, the GLA handed the baseline survey data to the evaluation team. The evaluation team then completed eligibility checks based on answers to the baseline survey and verification of online sources (e.g. Companies House information and company websites). Randomisation was then carried out on the sample of eligible firms. We stratified by subsector (retail versus hospitality) and firm size band (under 10 employees and 10 employees or over). We performed the randomisation using STATA software, and set the randomisation seed to ensure replicability. To deal with uneven numbers in some strata, "misfits" were randomised following code written by Bruhn and McKenzie (2011).[18]

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[16] Data from 2017 were available in the UKDS when this analysis was conducted. Data from 2018 are now available. Reference: Office for National Statistics. (2017). Business Structure Database, 1997-2017: Secure Access. [data collection]. 9th Edition. UK Data Service. SN: 6697, http://doi.org/10.5255/UKDA-SN-6697-9

[17] These are: employment <=250, revenue < £50 million (SME definition), business is live and older than 1 year old; turnover is greater than zero: and those with SIC codes of 47: Retail trade except sale of motor vehicles; 55: Accommodation; and 56: Food and beverage service activities.

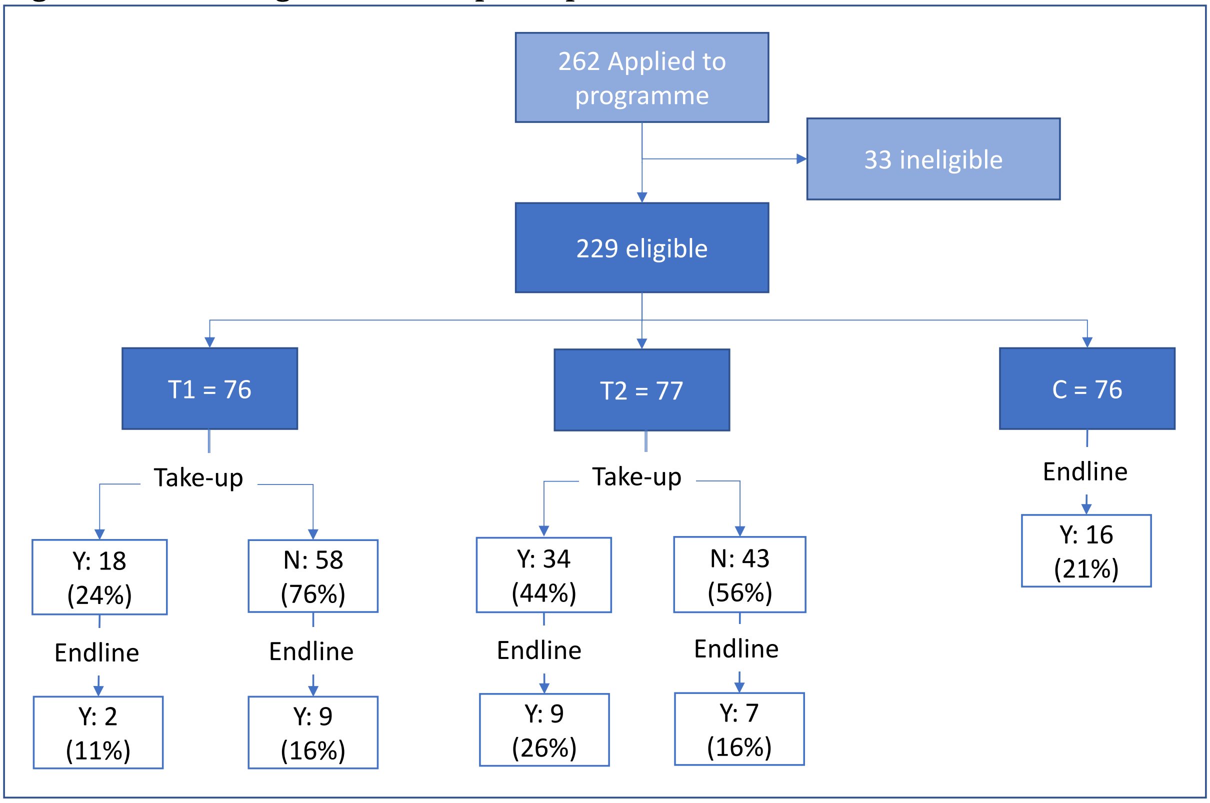
[18] https://blogs.worldbank.org/impactevaluations/tools-of-the-trade-doing-stratified-randomization-with-uneven-numbers-in-some-strata

We found that the three groups were broadly balanced across key business and respondent characteristics, market characteristics, and baseline technology questions (attitudes, previous adoption patterns and intentions), as shown in Appendix Table A1. It does appear that at baseline, T2 firms had higher ambition for revenue growth, and considered information to be a stronger barrier to AI technology adoption, on average, compared to both T1 and the Control group. T2 firms also had higher self-reported digital capabilities compared to the Control group. We also conducted "omnibus tests" of joint orthogonality,[19] where treatment status is regressed on the full set of characteristics described in Appendix 1, and did not find significant F-statistics for any of the three treatment groups.

3.4. Take-up and attrition

Of the 229 firms that signed up for the programme, and that were randomised across the two treatment arms and control group, we had a low take-up of the interventions and a very low share of firms across all groups filled the endline survey (43 of the 229 firms, representing attrition of 81% across the sample). Figure 2 summarises take-up and follow-up (completion of the endline survey) for each group (a breakdown by cohort is given in Appendix Table A2).

Figure 2: Converting recruits into participants



Notes: Take-up is defined as attending the programme event in the T1 group, and either attending the event or attending/booking a one-to-one in the T2 group. No control group firms had access to the treatments as they were by invitation only. Across all arms, 43 firms completed the endline survey.

We were aware of the low take-up of the treatments at the time of our Pre-Analysis Plan, but set out our plans to conduct an Intention to Treat (ITT) analysis, highlighting concerns regarding power in the scenario of 50% attrition which we viewed as a pessimistic case. With

[19] https://blogs.worldbank.org/impactevaluations/tools-trade-joint-test-orthogonality-when-testing-balance

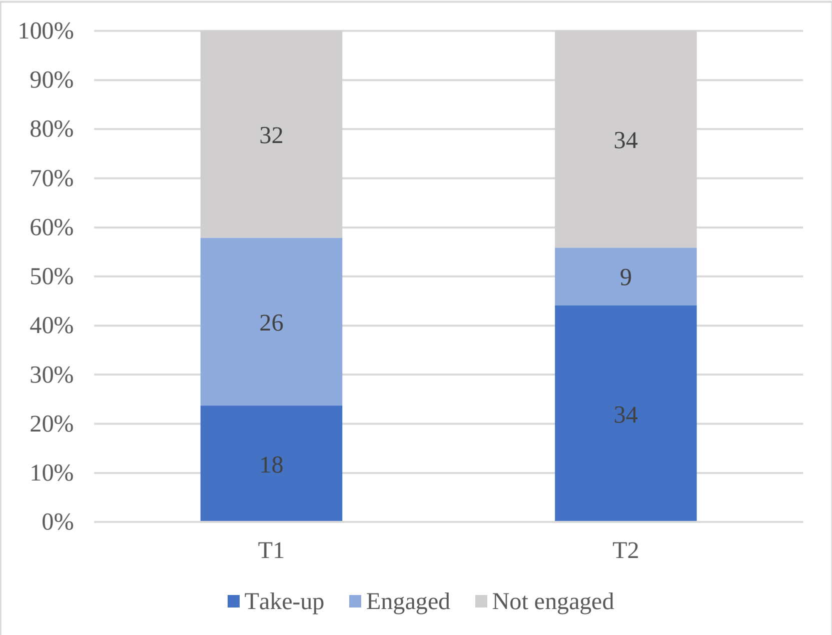
endline data on only 43 firms across the three treatment groups (representing 81% attrition), we have been unable to perform robust econometric evaluation of the programme and therefore focus on more of a descriptive analysis in this report.

Take-up of treatment

Take-up rates were low across both treatment arms and cohorts. Our implementation partners found it particularly challenging to ensure that all the firms invited to the events attended them. Once we had randomised firms to treatment arms, firms received an e-mail from the GLA informing them of their group, and T1/T2 firms were informed that CognitionX/Capital Enterprise would be in touch shortly with details. All groups, including the control group, received the "Guide to AI" as a link in this e-mail. The lists of SMEs allocated to T1 and T2 were passed to the implementation partners, who then e-mailed, called and or messaged the contacts who had given their details in the baseline survey.

Figure 3 summarises the take-up of the programme across the two treatment groups. Only 18 out of 76 (24%) and 34 out of 77 (44%) of firms of Treatment 1 and Treatment 2 respectively took up the treatment (this difference is statistically significant with a p-value of 0.007). We note however that here take-up for T2 includes SMEs that either attended the event or attended/booked a one-to-one with the caseworker (see Appendix Table A3 for a more detailed breakdown of the data underlying this, by cohort). Comparing T1 take-up with only the event attendance in T2 (25 firms only attended the event, representing 33% of the sample), the difference is not significant at conventional levels (p-value 0.23).

Figure 3: Take-up and engagement in the programme in treatment groups



Notes: Participation (take-up) is defined as attending the programme event in the T1 group, and either attending the event or attending/booking a one-to-one in the T2 group. "Engaged" firms were those that showed interest in the programme, or signed up for the events, but could not make it on the day. The data labels represent the number of firms in each category. 76 firms were allocated to T1 and 77 firms were allocated to T2 in total.

Figure 3 also highlights the firms that engaged in the programme, but did not attend (this includes firms that signed up for the event but did not attend, or that showed interest in the programme but could not make the events). 26 firms were in this category in the T1 group

(34%) and 9 in the T2 group (12%). Across both groups, a large share of firms – nearly half – did not engage with the programme. Firms in this category were either non-contactable, stated that they were no longer interested in the programme, or would not commit to involvement.

Feedback from our implementation partners highlighted some of the difficulties involved in converting recruits into participants. Some SMEs claimed that despite signing up to the programme, they did not really understand what the project entailed. This is likely to be a function of the way firms were recruited, via "cold calling" and being directed to the project website for entry into the randomised control trial, as opposed to seeking out a programme of support to meet their needs. In T1 in particular, quite a large number of SMEs showed interest in the programme but could not make the events. As a team, we were responsive and tailored our approach as the programme progressed. Where firms from earlier cohorts were interested in the programme, we gave them the option to join later cohort events. Section 5.3 details programme feedback from the perspective of the implementation partners, and draws out lessons for the design of future business support programmes.

Appendix Table A4 compares baseline characteristics of firms that participated in the programme with those that dropped out for T1 and T2 separately (Panel A), and for all treatment firms pooled together (Panel B). There are a number of dimensions on which firms that participated in the programme differ significantly from those that dropped out. Retail firms were more likely to participate than hospitality firms, and this difference is significant in T1. Also in the T1 group, firms that participated were significantly larger in revenue terms (on average three times larger), were more likely to consider the competition they faced to be fierce, and considered a lack of information on technology providers to be more of a barrier to adoption than those that dropped out. There were also significant differences on the technology outcomes variables asked at baseline: participants in T1 events considered themselves more likely to adopt AI (this is the most significant difference), and had more positive attitudes towards AI (being more likely to consider that AI would lead to increased revenues and customers).

In the T2 group, different variables appear to relate to participation. Smaller businesses were significantly more likely to participate. Firms that participated were more likely to have a female manager, and a manager that held a degree, and they were more likely to have reported that the business had grown in revenue terms compared to the firms that dropped out. Participants were less likely to consider resistance to change by managers or employees to be barriers to adoption, but there were no other differences across technology variables including attitudes.

Pooling treatment firms together, smaller firms with managers holding a degree were overall more likely to participate, as were those that considered information on technology providers and management or workforce skills to be major barriers (and less likely to consider resistance to change from staff or macro uncertainty to be major barriers). Participating firms were overall more likely to adopt AI at baseline and to consider that AI would have a positive impact on the business. These differences are significant at the 10 per cent level.[20]

Follow-up (endline) survey

[20] An F-test of joint significance on all these variables predicting participation in the pooled sample (where all baseline covariates are available) yields significance at the 5 per cent level. The equivalent F-tests for each group separately are not significant.

This programme experienced very high loss-to-follow-up across treatment and control groups. The initial plan for conducting the endline surveys was to send e-mails out to the relevant contacts who had signed up for the programme and/or engaged with our implementation partners. However, we soon realised that response rates were too low following this method, so, again, we employed Integral Research to assist us, calling the SMEs to remind them about the endline survey, and giving them the option to complete it over the phone. Despite numerous attempts, response rates remained low. After the telephone campaign was closed, the LSE evaluation team again sent personalised e-mails to each participant in the programme highlighting the importance of hearing their views, so that future support programmes can be better designed to meet their needs. Given the disruptions faced by our target firms at this time due to Covid-19 (illustrated in Figure 11), we can conclude that providing feedback on this programme was not a priority.

Table 3 summarises the endline survey response rates by group, and shows that the differences are not statistically significant (Appendix Table A5 tests for attrition in a regression framework, and again finds that attrition is not significantly related to treatment status, controlling also for the randomisation strata and cohort fixed effects).

Table 3: Endline survey response rates by group

	T1	T2	C	Total
Baseline	76	77	76	229
Follow-up	11	16	16	43
Response rate	14%	21%	21%	19%
p-values tests of equality of response rates				
T1 vs C	0.292			
T2 vs C	0.967			
T2 vs T1	0.309			

Notes: Reported p-values from t-tests of equality of endline survey response rates.

We also consider whether the firms that filled the endline survey differ from the attritors based on observable characteristics (Appendix Table A6). We find that non-attritors are similar to attritors on most observables, but there are a number of significant differences. In particular, non-attritors were more likely to have a female manager, or a manager with a degree, and they were more likely to consider themselves as having strong digital capabilities. In terms of barriers, they were more likely to consider information on technology providers to be a barrier to adoption, but less likely to consider applicability to the business or resistance to change by managers or workers to be barriers. They were also more likely to consider that AI would have a positive impact on the business, and that decisions to adopt AI would be influenced by others in their sector. So overall it does appear that the firms for which we have endline survey data have a more positive view on the relevant technologies, and rate some of the barriers that the programme was seeking to address more highly. An F-test for joint significance of the variables included as predictors for filling out the endline (in Table A6) yields significance at the 5 per cent level.

We proceed to consider whether the non-attriting sample was balanced on baseline characteristics across the treatment groups (Appendix Table A7). We find that, overall, the sample of non-attritors is relatively well-balanced on baseline characteristics, but there are a number of differences. In particular, the T1 non-attritors appear to be significantly more likely to have already conducted a cost-benefit analysis on AI technologies relative to both T2 and the control group, and less likely to consider resistance to change by managers or staff to be a barrier to adoption compared to T2 and to the control group. The T2 firms appeared to have less-positive attitudes towards AI in terms of its ability to increase revenues or customers, particularly in comparison to the control group. Such differences imply that extra caution is needed when comparing outcomes across the treatment groups, and suggest that controlling for technology-related variables available at baseline would be necessary in econometric specifications.

Qualitative interviews

We complement our analysis of the endline survey with qualitative analysis of interviews with a sample of programme participants, conducted by an expert in qualitative research methods. Given our low endline response rates, which occurred despite numerous rounds of chasing, we decided to approach only firms that had completed the endline survey (i.e. those that had engaged with the programme to some extent) to see if they would be willing to take part in an interview.[21]

Four firms agreed to participate: one firm was from the control group, two firms from T1 and one from T2. Three of the sample were in the retail sector and one in hospitality. All of them were microbusinesses (fewer than 10 employees), and therefore were in our “small” stratum. The interviewees were either the founders or co-founders of their companies, currently acting as CEOs or directors.

Interviews lasted between 30 minute to one hour, and were conducted over Zoom or by phone. They covered four broad themes: programme feedback, technology adoption, insights for future policy and programmes, and the impacts of Brexit and Covid-19 on technology adoption.

3.5. Approach to evaluation

We set out our intended approach to evaluating the programme in the Pre-Analysis Plan (Valero, 2019). The primary analysis would compare outcomes for each treatment group to the control group in turn (and to each other) in an Intention to Treat (ITT) analysis as follows:

$$Y_{i,c} = \beta_0 + \beta_1 T_i + X_i\delta + ch_c + s_i + \varepsilon_{i,c} \quad (1)$$

Where $Y_{i,c}$ denotes the technology-related outcome (see below for a full description) for firm i in cohort c, T_i the treatment assignment, ch_c cohort fixed-effects and s_i strata dummies. Where a particular outcome was asked at baseline, we planned to incorporate its baseline value within the controls X_i.

Our pre-analysis plan contained power calculations based on the full sample of 229 and an initial assumption of 50% attrition (see Appendix 2 for a summary, where we update for the

[21] We initially planned to interview 9 firms (spread across cohorts and treatment arms). Firms were contacted by e-mail following a stratified randomised ordering to minimise discretion in the selection process. However, due to the low response rate, all firms that had completed the endline survey were eventually contacted.

sample, we achieved at endline). With attrition of 81%, our planned statistical analysis is severely underpowered. Moreover, we have seen that on some variables the attrition was also non-random. In this report, our focus is therefore on a descriptive analysis of our baseline and endline data and our follow-up qualitative interviews. We provide the results from estimating equation (1) on the outcomes described below, adding also outcomes at baseline (where applicable), in the Appendix. As expected, these did not yield significant treatment effects.[22]

The primary outcomes of interest (as set out in the Trial Protocol and Pre-Analysis Plan) were designed to test whether the treatments were effective in helping firms move along the stages of technology adoption (BEIS, 2019), and this was captured across three primary outcomes (PO1-3). The third measure was actual adoption (or the decision to adopt). The first and second sought to pick up movement towards this stage, as follows:

- **PO1: Technology assessment process:** Answer to the question "Have you allocated staff time or resource to exploring the possible adoption of chatbots / marketing automation technologies?" (binary variable 0,1). This variable was asked at baseline and endline, and provides information on whether firms are committing resources to moving forwards within the persuasion stage.
- **PO2: Intentions to adopt chatbots/marketing automation technologies:** Answer to the question "How likely are you to adopt chatbots/marketing automation technologies over the next 12 months?" (score, 1=very unlikely, 5=very likely). This variable was asked at baseline and endline, and provides information on whether firms are moving from persuasion towards decision.
- **PO3: Actual adoption of chatbots/marketing automation technologies/ decision to adopt**: Answer to the question "Have you adopted, or taken the decision to adopt, a chatbot/marketing automation technology over the past 6 months?" (binary variable 0,1). This variable was asked only at endline (since a lack of previous adoption was one of the eligibility criteria), and provides information on whether a firm has moved into decision/implementation.

We also set out a series of secondary measures, which were intended to allow us to explore mechanisms and wider impacts of the programme.

- **SO1: Attitudes towards chatbots/marketing automation technologies:** We asked a series of questions at baseline and endline which sought to capture the respondents' attitudes towards the relevant AI technologies. The questions were phrased "Please indicate whether you agree with the following statements (score, 1=strongly disagree, 5=strongly agree): "I have a good understanding of the costs and benefits of chatbots and marketing automation technologies"; "Chatbots or marketing automation technologies would lead to increased revenues; profitability; customers"; "Chatbots or marketing automation technologies would have a positive impact on the day to day running of my business"; "My decision to adopt chatbots or marketing automation technologies is influenced by what other businesses in my sector are doing."

[22] In our PAP, we also envisaged adding a vector of relevant control variables X_i to the analysis which we expected to increase precision and control for any imbalance at baseline, and for conducting "on treatment" analysis, and analysis of heterogeneity by key firm characteristics. We have not conducted these extra analyses given the low sample size.

- **SO2: A measure of the change in intentions to adopt chatbots / marketing automation technologies:** "Are you now more likely to adopt chatbots / marketing automation technologies than before the intervention?" (binary variable 0,1). This variable would be useful in the case of low adoption rates, but where a high proportion of SMEs stated that they were likely to adopt in the baseline survey.
- **SO3: Broader adoption of technologies or innovative organisational practices/ decision to adopt:** "Have you adopted, or taken the decision to adopt, any other innovative technologies or innovative organisational practices over the past 6 months?" (binary variable 0,1). This variable was asked at baseline and endline, and provides information on whether a firm has moved into/committed to a decision/implementation in a broader sense.

In this study, we are considering a multitude of outcome variables to try to capture firms' journeys through the stages of technology adoption. We therefore compute aggregated indices to assess whether there is any evidence of an overall programme impact on the outcomes of interest. To maximise transparency and readability, we do this for the adoption-related binary outcomes (PO1, PO3, SO2, SO3) and the attitudes-related outcomes, which are scored 1-5 (PO2, SO1) separately, taking a simple average across each group of outcomes respectively.

4. Describing our sample using the baseline survey

In this section, we describe key characteristics of the full sample at baseline, and relevant insights that these data generate regarding barriers and attitudes towards AI technologies. Section 3.3 discusses the balance checks we carried out on the baseline sample (and a comparison of treatment group means across key variables is provided in Appendix Table A1).

Table 4 summarises some key characteristics of our sample at baseline. 62% of the sample are in retail and the same share were classed as "small" (under 10 employees in this context). Around two thirds of respondents were male, and had a university degree, respectively, and around half of the sample were under 40. The average firm had 16 employees, and revenues of £151,000. Large shares of the sample reported growth in terms of employment (42%) or revenues (62%), and even larger shares of firms had ambitions to grow in the future (85% in employment terms, and 94% in revenue terms).[23] Firms in our sample were not over-confident, with just 30% considering themselves to be more productive than their peers.[24] The majority (69%) considered themselves to be operating in competitive markets.

Overall, firms did not seem too advanced in terms of their use of technology or related capabilities. 24% considered themselves to have strong digital capabilities, and 20% strong marketing capabilities. Just 11% had already conducted a cost-benefit analysis on chatbots and marketing automation technologies. However, 27% were aware of their competitors using such technologies.

[23] These shares are slightly higher than those found in the Small Business Survey, where in 2019, the share of SME employers that wished to grow sales over the next three years was just under 80% for Retail, and nearly 75% for Accommodation (BEIS, 2019).

[24] This is much lower than the 79% of businesses that were found believe that they are at least as productive as their peers in an analysis conducted by Be the Business (2018).

Table 4: Summary characteristics at baseline

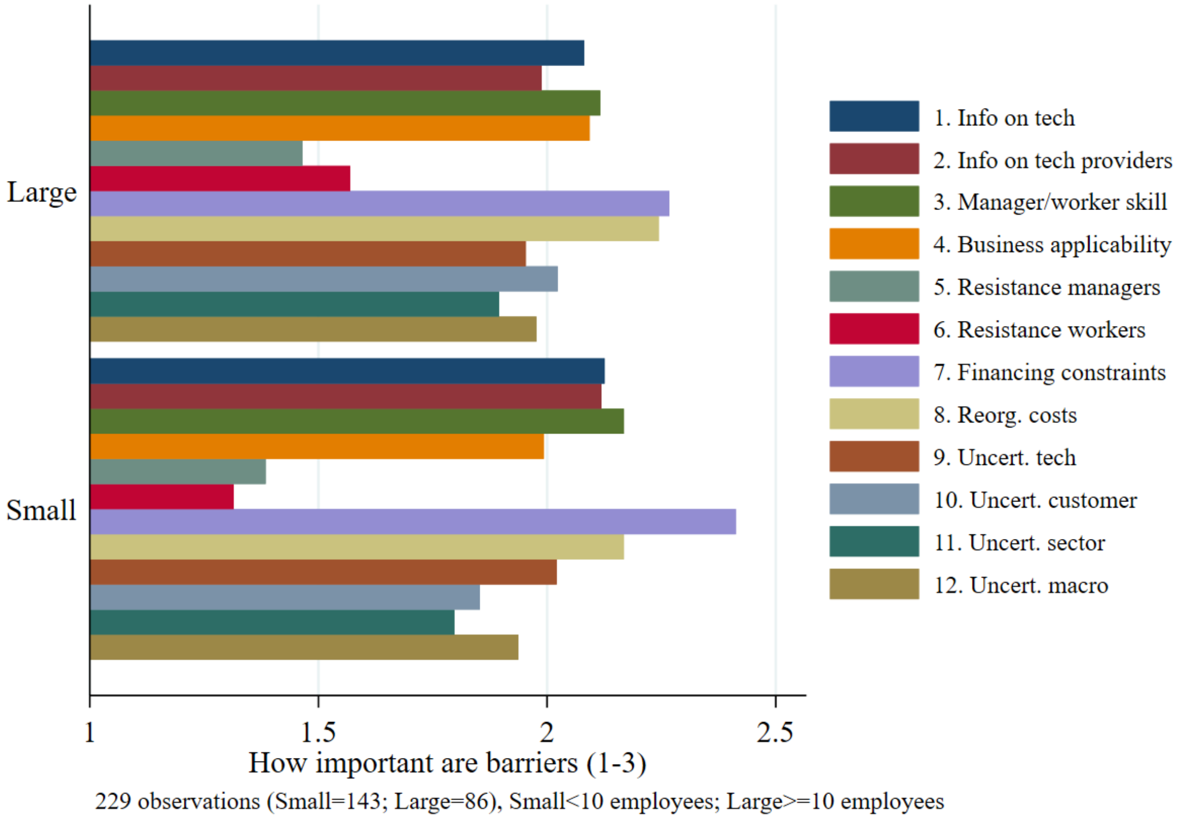
	Mean	SD	N
Retail	0.62	0.49	229
Small	0.62	0.49	229
Manager- male	0.64	0.48	228
Manager- has a degree	0.66	0.48	229
Manager- Under 40	0.49	0.5	227
Employees (#)	16.24	34.95	229
Employment has grown	0.42	0.5	229
Employment growth ambition	0.85	0.36	229
Revenue (£000)	151.09	362.16	208
Revenue has grown	0.62	0.49	229
Revenue growth ambition	0.93	0.25	229
More productive than competitors	0.3	0.46	229
Competition considered fierce	0.69	0.47	229
Strong digital capabilities	0.24	0.43	229
Strong marketing capabilities	0.2	0.4	229
Conducted CBA on AI tech	0.11	0.31	229
Competitors use AI tech	0.27	0.44	229

Notes: Employment or Revenue growth ambition are dummies=1 answered that they would want to see their business slightly or significantly larger than its current size on each measure respectively (Q29 and Q31, baseline). Competition considered fierce is a dummy=1 if companies consider themselves to face intense of very intense competition (Q35, baseline) or that if they were to go out of business, competitors would take up all of their sales (Q37, baseline). Companies were considered to have strong digital or marketing capabilities when they rated themselves 4 or 5 out of 5 (Q42, 43, baseline).

In order to understand the extent to which the barriers we set out in Table 1 were important for our sample, we asked firms to give each a score between 1 and 3, where 1 is not an obstacle, 2 is a minor obstacle and 3 is a major obstacle. The results are in Figure 4. Interestingly, the top three ranked barriers relate to financing constraints (the costs of new software and reorganisation) and skills, and these findings are consistent with the reported barriers to technology adoption more generally in Riom and Valero (2020) on a broader set of businesses across sectors, size bands and UK regions (and findings in the UK Innovation survey[25]). Figure 4 splits the sample into larger and smaller businesses, and while the overall profile of barriers appears similar, smaller firms are more likely to report that financing constraints are key barriers to adoption, and less likely to report resistance from workers as a barrier.

[25] In the latest UK Innovation Survey (UKIS, 2019), figure 7.1 shows that the top-rated barriers to broader innovation tend to be finance-related (and include financing constraints, innovation costs being too high, financing costs) and a lack of qualified personnel appears particularly important in the latest survey, together with economic risks and the outcome of the EU referendum.

Figure 4: Self-reported barriers to AI adoption at baseline



Notes: Barriers scored on a scale 1-3, where 1=not an obstacle, 2=minor obstacle, and 3=major obstacle. Barriers are abbreviated from the following: 1. Lack of information on chatbots/marketing automation applications and uses; 2. Lack of information on technology providers; 3. Lack of required management/workforce skill; 4. Business specific doubts over applicability - i.e. whether sales/marketing tasks can be automated; 5. Resistance to change from management; 6. Resistance to change from employees; 7. Financing constraints (regarding investment - e.g. software costs); 8. Costs of reorganisation (training, reallocating tasks); 9. Uncertainty in technology market - rapid change, potential for lock-in; 10. Uncertainty over impacts on customers and hence revenues (e.g. privacy concerns); 11. Uncertainty over relevance and demand amongst SMEs in sector; 12. Uncertainty about macroeconomic outlook (e.g. Brexit)

We asked a number of our outcome questions at baseline with the intention of examining changes at endline. In particular, we asked whether businesses had already allocated staff time or resource to exploring the possible adoption of chatbots/marketing automation technologies (PO1). We found that 19% of the sample had already done this upon signing up to the programme. And on PO2, the likelihood that the business will adopt chatbots/marketing automation technologies over the next 12 months (scale 1-5, where 5 is highest), the mean answer was 3.06. We also asked how much firms were willing to pay per month to adopt chatbots or marketing automation technologies, and while many firms did not answer (100/229), the average for those that did was £453, which is actually larger than typical monthly subscription rates for many of the eligible technologies.

Table 5: Summary technology questions (outcomes) at baseline

	Mean	SD	N
PO1- Resource allocated to exploring AI	0.19	0.39	229
PO2- How likely to adopt AI (1-5)	3.06	1.29	229
SO1- attitudes, good understanding of AI (1-5)	2.05	1.19	229
SO1- attitudes, AI leads to increased revenues (1-5)	3.3	1.12	229
SO1- attitudes, AI leads to increased profits (1-5)	3.3	1.09	229
SO1- attitudes, AI leads to increased customers (1-5)	3.41	1.12	229
SO1- attitudes, AI has positive impact on business (1-5)	3.44	1.15	229
SO1- attitudes, AI influenced by other firms in sector (1-5)	2.66	1.23	229
SO3- Introduced new broader tech/practices in last 6m	0.36	0.48	229

Notes: Summary out outcome variables asked at baseline, explanation given in Section 3.5.

We asked businesses a series of questions relating to their attitudes towards chatbots and marketing automation technologies (SO1). The answers reveal that businesses did not consider themselves to have a good understanding of the costs and benefits of these tools (average score 2/5). On average, firms were relatively positive about the potential or these technologies to lead to increased revenues, profits, customers and have a positive impact on the business (all of these had average scores around 3.3-3.4 out of 5).

Around a third of the sample (83 firms) had introduced other innovative technologies or organisational practices over the past 6 months (SO3). Varied examples were given, and included multiple references to CRM, upgrading websites and new software packages.

5. Evaluating the programme

5.1. Analysis of endline survey data

In this section, we provide a quantitative analysis of the endline survey data, based on a sample of 43 for which all core variables are non-missing. We begin by describing the key outcomes, summarising these by treatment group, before proceeding to analyse some wider variables of interest, including programme feedback and impacts of Covid-19 on business operations and technology decisions.

AI technology outcomes

As we set out in Section 3.5, this study is underpowered. Indeed, as we expected given ex-ante power calculations, estimating regressions as per equation (1), excluding or including outcomes at baseline (where available), does not yield significant results. Such regressions are reported in Appendix Table A8 for reference. We provide a discussion of the impact of attrition on our minimum detectable effect and our regressions in Appendix 2.

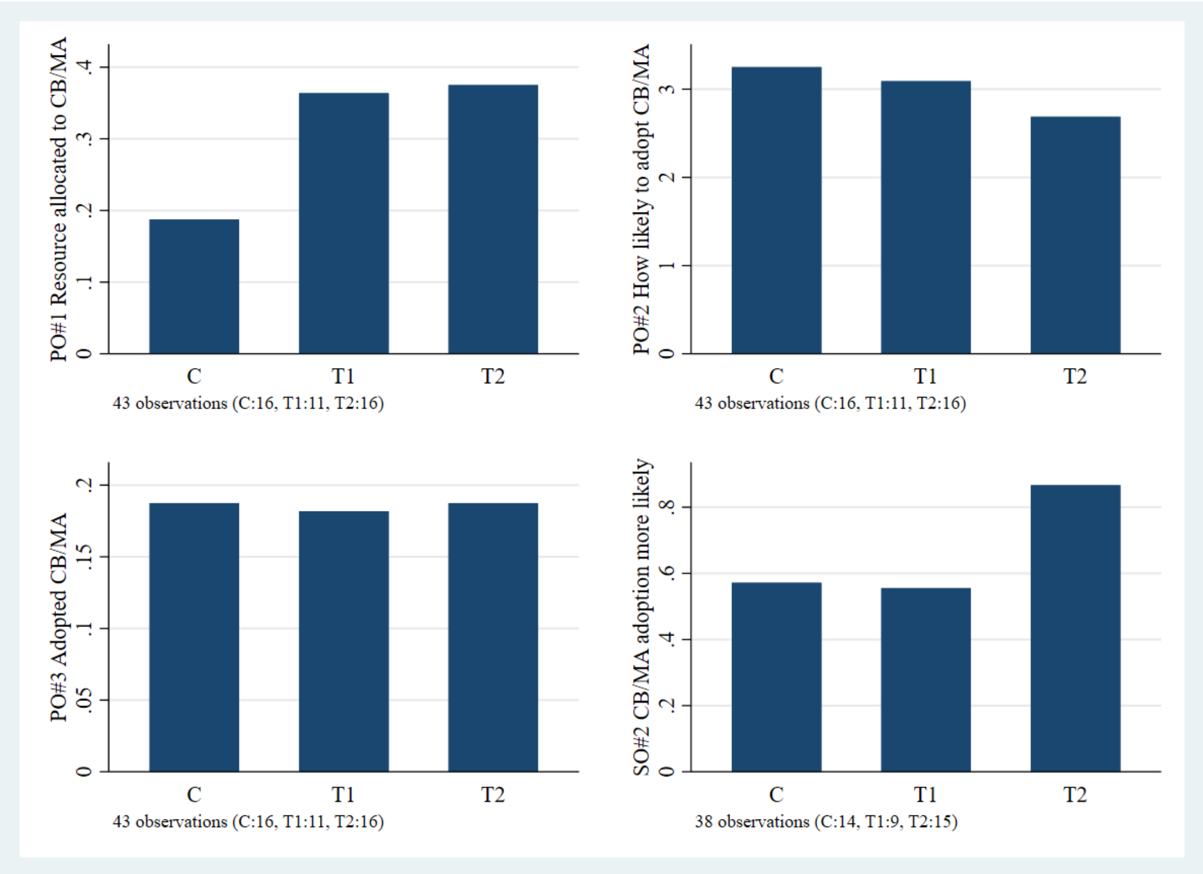
In this section, we therefore provide a basic description of the data that we have obtained in the endline survey, plotting group averages for key variables, while noting that we cannot draw robust conclusions about the effectiveness of the programme based on the available data at endline.

Figure 5 plots the key AI adoption-related outcomes across the three treatment arms. The first primary outcome (PO1) is a binary variable of the "technology assessment process", or whether the firm allocated staff time or resource to exploring the possible adoption of chatbots and marketing automation technologies. Across the 43 firms that completed the outcome questions in our endline survey, 30% responded that they had allocated resources in this way, with the positive response being higher in the two treatment groups. In a follow up question for the 13 firms that did allocate resource, over half specified that they had spent over 10 hours on this issue. On this measure, activity in the two treatment arms appears to be higher than in the control group.

The second primary outcome (PO2) measures the intentions to adopt chatbots and marketing automation technologies over the following 12 months. It asked how likely the firm was to adopt such technologies on a 5-point Likert scale. Here we see that actually the respondents in the control group considered themselves marginally the most likely to adopt.

The third primary outcome (PO3) is a binary variable and measures whether firms actually adopted or had taken the decision to adopt a chatbot and marketing automation technology over the past 6 months. Across the sample, 19% stated that they had actually adopted these technologies, and this does not differ across respondents in the different groups. Of the 8 businesses that adopted, 4 mentioned chatbots when asked the type of technology.

Figure 5: AI adoption related outcomes (PO1-3, SO2)



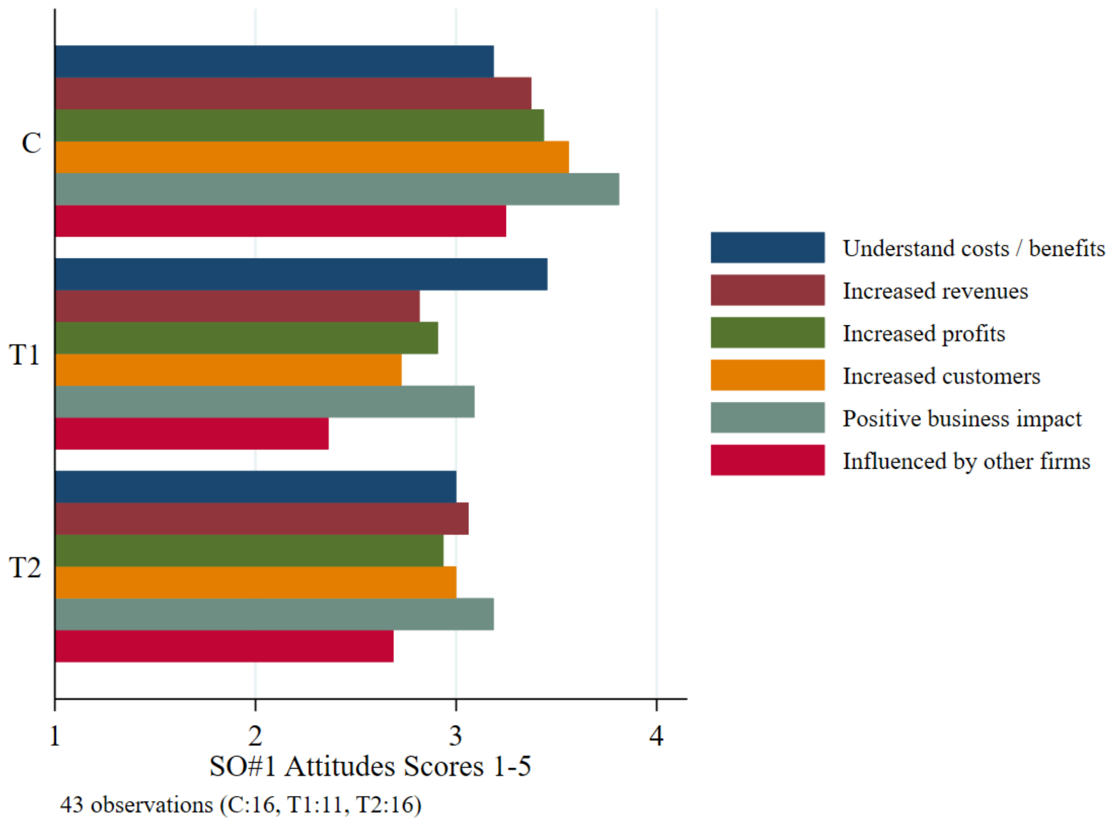
Notes: Technology adoption outcomes at endline, summarised by group.

We also asked whether there had been a change in intentions to adopt chatbots and marketing automation technologies (SO2). Here, the share responding positively was highest in the T2 group (in fact, the difference between T2 and the control group is the only difference that was both positive and significant - at the 10 per cent level - in the regression analysis, see Appendix

Table A8, Panel B. It must be noted, however, that with multiple outcomes, it is likely that a significant result is obtained by chance. In addition, a statistically significant result found in an underpowered, small-sample study is likely to be misleading (Gelman et al., 2014).

Interestingly, at endline we find that attitudes towards AI were overall more positive in the control group, though the T1 group appear to have developed a better understanding of the costs and benefits of relevant AI technologies.

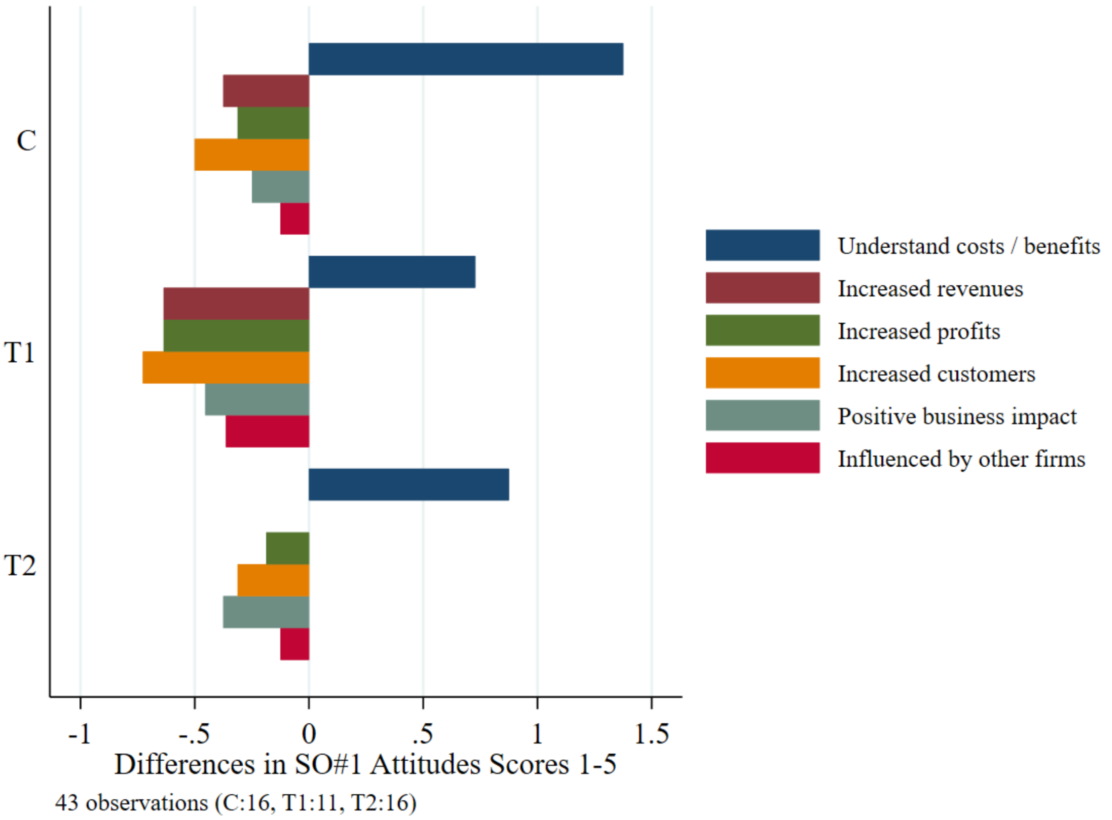
Figure 6: Extent to which the firm agrees with statements related to Chatbots and Marketing Automation technologies



Notes: Technology attitudes outcomes at endline, summarised by group. Scores between 1-5 (1= strongly disagree, 5=strongly agree) on a series of statements relating to chatbots and marketing automation understanding, impacts on business, and the final statement relates to the decision to adopt (being influenced by other firms in sector).

We also calculated the difference between endline responses and baseline responses for firms that answered both, and describe the averages of these changes by group in Figure 7. Across all groups, firms revised downwards their attitudes towards AI, especially among T1 firms. T2 firms revised their beliefs downwards the least, on average. We discuss differences according to whether firms attended the events or not below, however, the low sample size does not allow us to derive robust conclusions.

Figure 7. Change in Attitudes questions relating to Chatbots and Marketing Automation technologies



Notes: Differences in technology attitudes outcomes between baseline and endline, summarised by group. See notes to Figure 6 for description. Differences between endline and baseline scores for firms that answered both.

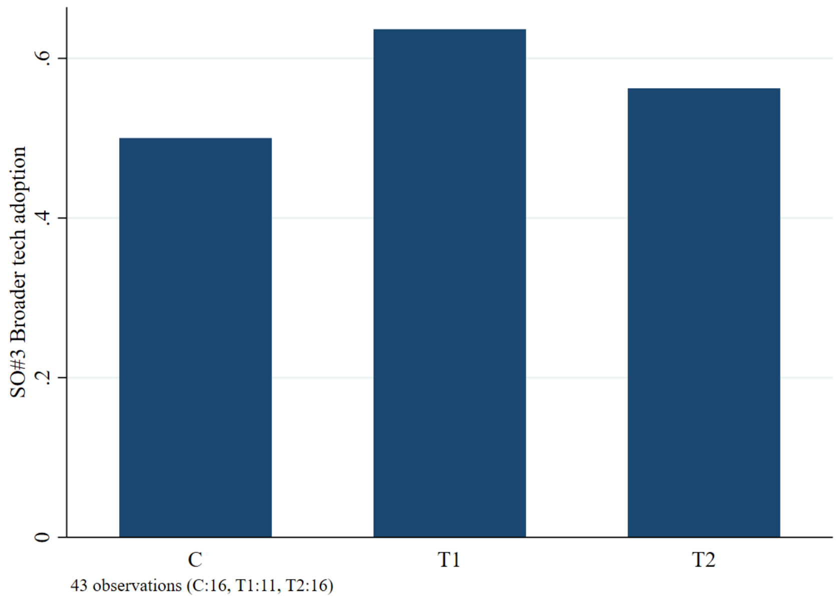
At endline, all firms report having a better understanding of the costs and benefits of chatbots and marketing automation technologies. Perhaps most surprisingly, control group firms report the highest improvement in their understanding of costs and benefits of AI between baseline and endline, and the increase is similar whether firms read the AI guide or not. This might be explained by two behaviours: firms "defying" their treatment group and seeking out external advice about AI (see Table 6), which might have been prompted by signing up to the programme and reading the "Guide to AI" or by external developments including the Covid-19 shock, or an "optimism bias" amongst control group firms, which might not have revised their beliefs in the absence of detailed information about the extent of the implementation costs of these technologies. However, the negative change in attitudes of non-participating firms in T1 and T2, described below, does not support the existence of an optimism bias in the rest of our sample.

It is however interesting to note that all other attitudes across treatment and control groups have become less "positive". Among T1 and T2 firms, this is driven by firms that did not participate in the programme. However, it is not possible to derive robust conclusions from this heterogeneity analysis given both the low sample size and the different event attendance rates between T1 and T2 firms.

Firms were asked their willingness to pay to adopt chatbots and marketing automation technologies. At baseline, many firms did not answer (100/229) and, on average, respondents were willing to pay £453 per month. While only 13 firms answered the question at endline, the average that firms were willing to pay was lower, at £335 per month. If we restrict the sample to firms which revealed their willingness to pay at both baseline and endline (10 firms), we observe a decrease in willingness to pay from £447 to £175. This could reflect macro factors and cash constraints in light of the Covid crisis. Interestingly, of these 10 firms, the 6 that did not participate in the programme reported a higher willingness to pay (£216 versus £114 for those that did participate). Given the small samples, it is hard to draw any firm conclusions from these patterns however.

The final secondary outcome relates to the broader adoption of technologies or innovative organisational practices. Overall, 56% of firms had engaged in broader adoption, and this share was high amongst respondents in the two treatment groups, especially among T1 firms. Of these 24 firms, 18 stated that the innovation was already implemented (for others it was in progress). This is about 50% higher than at baseline, where 36% of firms had introduced broader technology adoption in the last 6 months – and indeed this was likely to be driven by the response to Covid-19 (see further discussion of questions where we try to ascertain this explicitly below). The types of broader innovation listed related to business websites and online services improvements. Two firms had adopted augmented or virtual reality.

Figure 8: Broader technology adoption



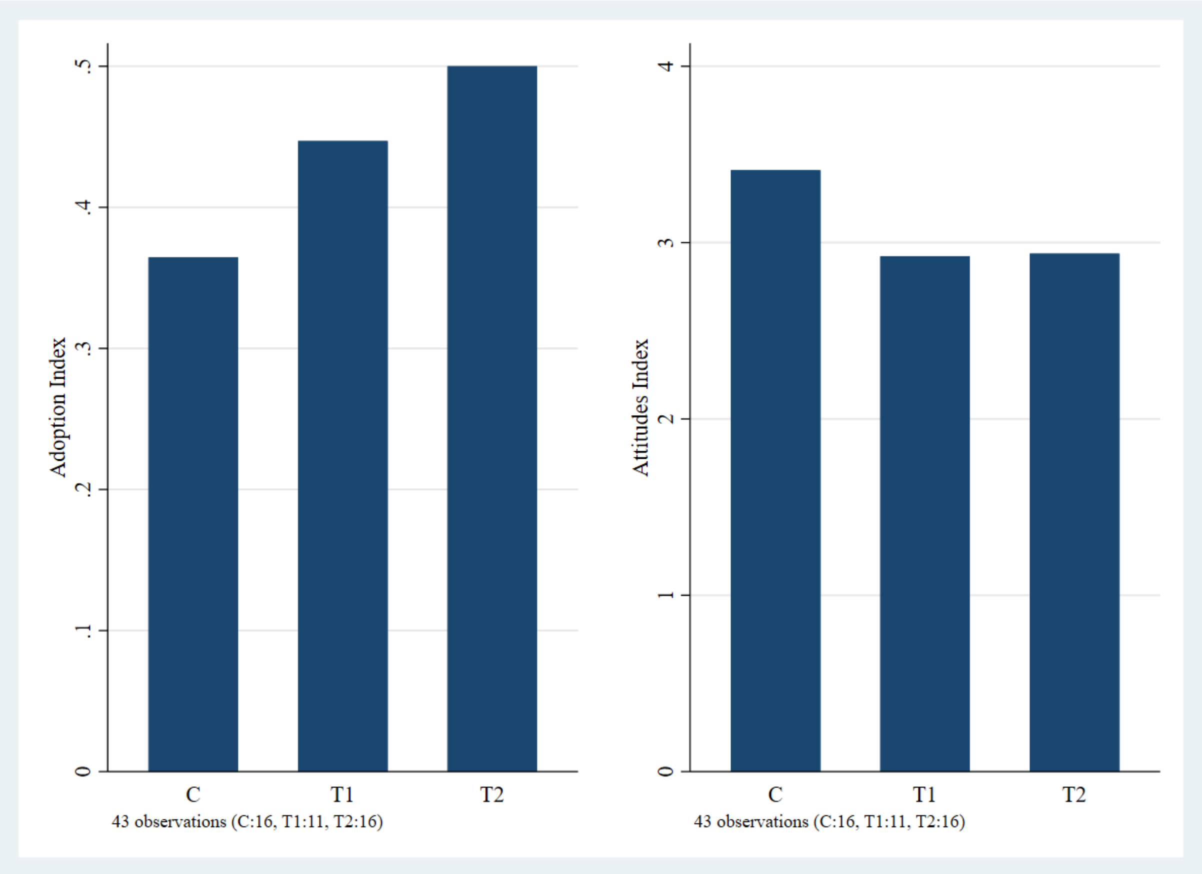
Notes: Broader technology adoption at endline, summarised by group.

Of the 19 firms that had not engaged in broader innovation, 11 said that they were now more likely to do so. Those that were not more likely to engage in broader adoption cited cost, lack of relevance and general business uncertainty as reasons.

Overall outcome indices

We aggregate the outcomes into two groups to generate adoption and attitudes indices by taking an average of scores across each. Adoption-related binary outcomes include PO1, PO3, SO2, SO3; and attitudes/intentions outcomes include all the attitudes questions (SO1), as well as the company's score (1-5) in response to the question "How likely are you to adopt chatbots / marketing automation?" (PO2). This suggests that, overall, adoption-related activity in the treatment groups was higher than in the control group, but attitudes/intentions towards AI appear to have shifted more in the control group. One hypothesis is that, given a high share of control group firms adopted general technologies during Covid-19 (Figure 13), this could have crowded out adoption of AI technologies.

Figure 9: Outcome indices



Notes: The adoption index treats as missing the five observations for which PO2 was not available.

External advice and "non-compliance"

We asked whether firms received any other type of advice on technology adoption outside of the programme. We found that all firms that answered the endline survey had sought external advice (this compares with around a third at baseline). The majority, 32 out of the 43 firms, obtained general technology advice (digital/IT), 8 obtained further advice on chatbots and marketing automation, and 3 sought advice on other AI technologies.

In principle, if firms across treatment groups had sought external advice of a similar quantity and quality, then the difference in outcomes would still be the treatment effect. But widespread take-up of external advice is likely to make the likely treatment effect smaller than it would have been if the treatment was the only source of advice available.

However, differential take up of external advice on chatbot/marketing automation specifically might impact our endline results as we are unable to disentangle whether any difference in outcomes is a result of our trial, of external advice, or a combination thereof.

In addition, control group firms that sought out external advice on chatbots/marketing automation or other AI technologies can be considered as non-compliers. As their non-compliance is self-selected, this could break initial randomisation. Given the low sample size, we do not carry out analysis to account for non-compliance, as suggested in the Pre-Analysis Plan, and instead present basic intention-to-treat estimates (Appendix Table A8), comparing each pair of groups in turn, and pooling treatment groups in comparison with the control group.

Table 6: External advice on technology

	C	T1	T2	Total
Chatbots/marketing automation	2	2	4	8
Other AI technologies	1	1	1	3
Other technologies in general (e.g. digital / IT)	13	8	11	32
	16	11	16	43

Notes: Breakdown of topic of external technology advice sought, by treatment group at endline (Q36, endline)

One potential explanation for the high quantity of external advice taken up is that the trial might have raised interest among firms for related technologies that were not in scope of the trial. The low sample size does not allow for any definitive conclusions, but the majority of firms sought advice for general technology rather than AI related products. This suggests that the trial did not change the priors of SMEs on the relative benefits of AI products relative to digital technologies more generally.

Perhaps a more likely reason for firms accessing external advice has been the impact of Covid-19 (Riom and Valero, 2020). We indeed find that a large share of respondents had reassessed their technology needs or adopted new technologies in response to the Covid-19 crisis (Figure 13). Dealing with the pandemic, associated business disruption, and reassessing broader technological needs might have crowded out the time and resource that would be required for SMEs to consider adopting the more “cutting-edge” AI technologies that were the subject of this programme.

Programme feedback

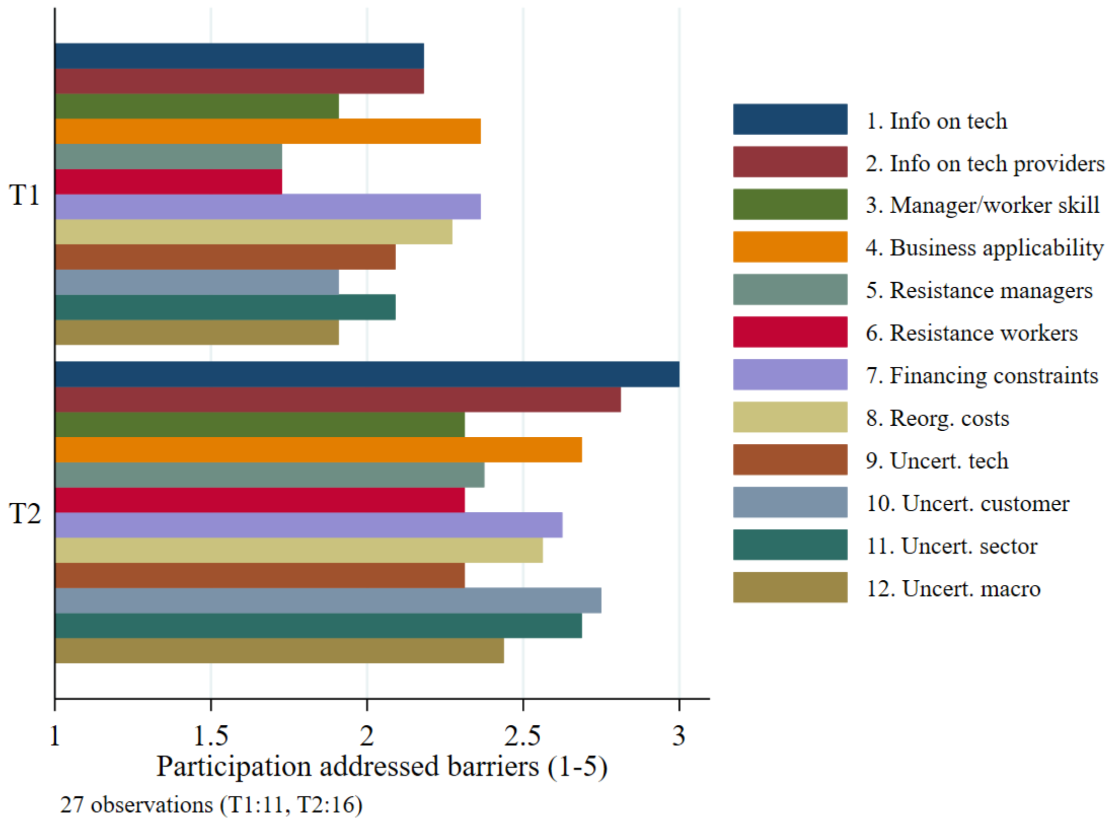
We asked all firms if they had read the “Guide to AI”, and of the 43 endline respondents, around half claimed that they had.

We have already seen that take-up of the events was low. Of those firms that attended the event and filled in the endline survey (11 firms across the treatment groups), the events were found to be useful overall (average score 3.73/5). The 7 firms which reported attending caseworker meetings and filled in the endline survey generally found these meetings to be useful (average score 3.71/5). The main reasons for not attending the events or the caseworker meetings were that firms were too busy and that these events were not a priority.

It is interesting to note that 44% of respondents stated that they planned to use the voucher in the endline survey. None of these went on to claim the vouchers before the programme close, however. Of those that did not plan to use it, the two main stated reasons were either that firms did not have the time to use it or that using the voucher was considered too complex.

We asked firms in the treatment groups the extent to which their participation in the programme addressed the 12 key barriers that we identified at baseline. As expected, and as set out in our Barriers Matrix (Table 1), due to the greater engagement and tailored advice offered in T2, firms in T2 considered that the programme addressed barriers to a greater extent than firms in T1. Firms in T2 found that the programme helped mitigate resistance to change from managers and workers significantly more than firms in T1.

Figure 10: Participation in the programme addressed barriers to adoption



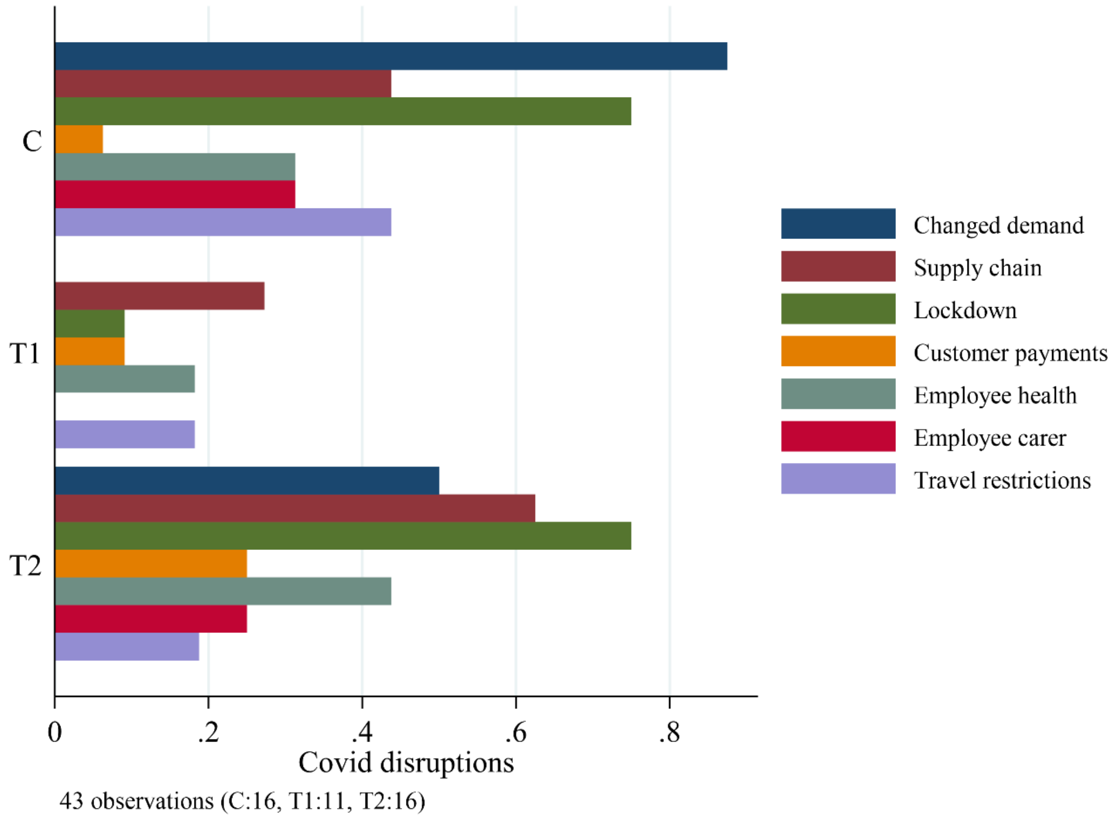
Notes: Summary of the extent to which participation address barriers, for the two treatment groups, scores 1-5, (1=to no extent, 5=to a great extent). Barriers are abbreviated from the following: 1. Lack of information on chatbots/marketing automation applications and uses; 2. Lack of information on technology providers; 3. Lack of required management/workforce skill; 4. Business specific doubts over applicability - i.e. whether sales/marketing tasks can be automated; 5. Resistance to change from management; 6. Resistance to change from employees; 7. Financing constraints (regarding investment - e.g. software costs); 8. Costs of reorganisation (training, reallocating tasks); 9. Uncertainty in technology market - rapid change, potential for lock-in; 10. Uncertainty over impacts on customers and hence revenues (e.g. privacy concerns); 11. Uncertainty over relevance and demand amongst SMEs in sector; 12. Uncertainty about macroeconomic outlook (e.g. Brexit)

Of the 27 firms that took part in the endline survey and were in the treated groups, 63% said that they would recommend the programme. We note that selection might play a large role in this result (and the broader programme feedback questions) if respondents to the endline survey are more likely than attritors to have had a good experience with the programme. Varied reasons were given and included either positive comments about the programme's informational value in helping dispel pre-held assumptions about AI, or negative comments on the fact that the technologies were not adapted to their business.

Covid impacts across the treatment groups

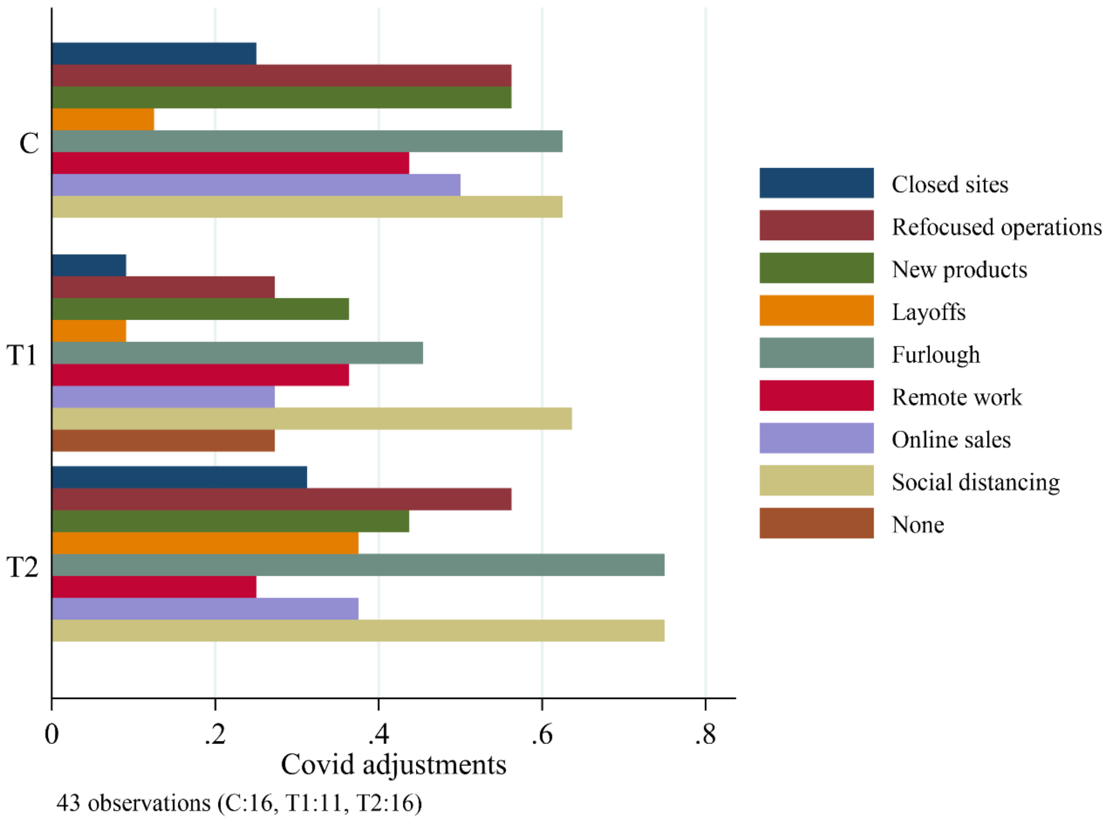
As shown in Table 2, our endline surveys were conducted during the second half of 2020. We therefore began the surveys with a series of questions relating to Covid-19 disruptions and responses, which might help explain differences in the impacts of the programme. We find that a large share of businesses reports various disruptions and adjustments made to their business operations due to Covid-19, and that such disruptions are not felt evenly across the treatment groups. Specifically, despite all firms being in retail and hospitality, only 10 to 25% of firms in T1 reported being impacted by various Covid-related disruptions, which is far fewer than firms in the control group and in T2. The most prevalent disruptions were lockdown restrictions, changed demand for products and services, and supply chain disruptions, which is again consistent with the findings in Riom and Valero (2020) on a wider sample of businesses across the UK.

Figure 11: Covid-19 disruptions



Notes: Summary of Covid disruptions, by group (firms ticked all that applied).

Figure 12: Covid-19 adjustments

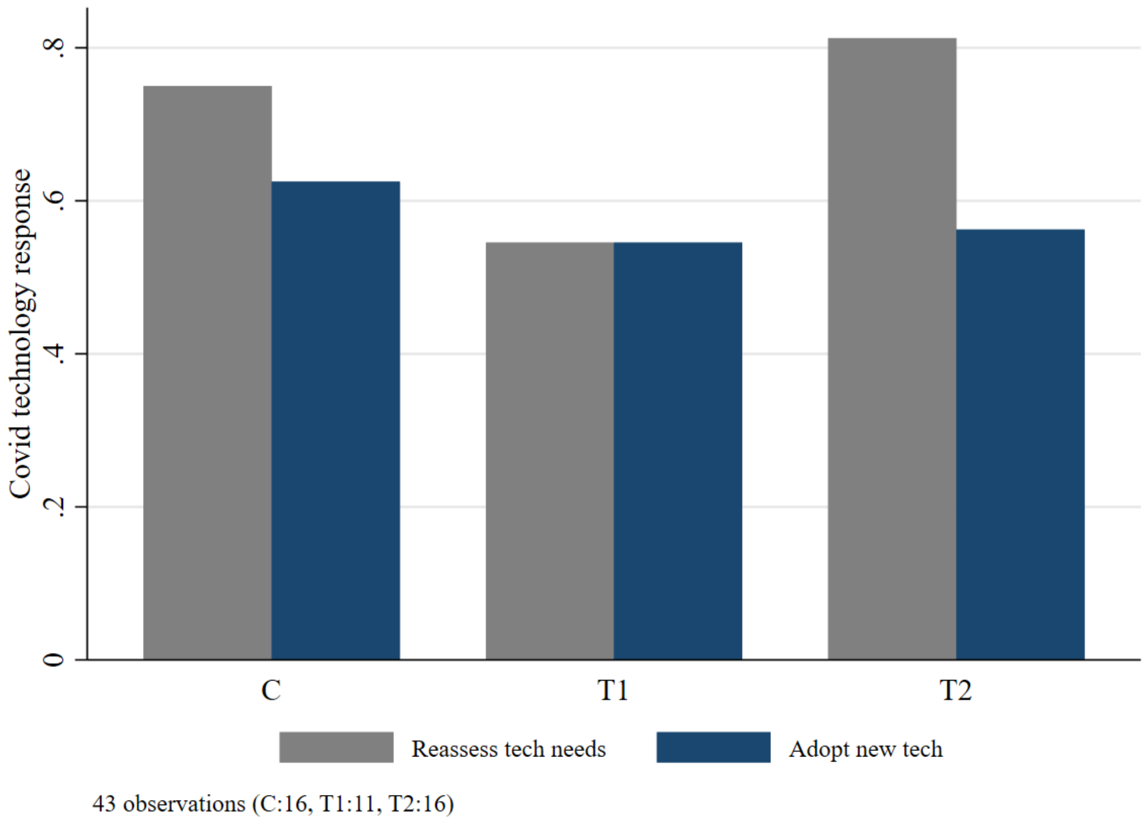


Notes: Summary of Covid adjustments, by group (firms ticked all that applied).

We also find widespread take-up of government support schemes in our sample. Across groups, over 40% of firms claimed government loans, around a third on average accessed grants, and around 20% of firms accessed the furlough scheme (there are some differences across groups here too).

Importantly for the purposes of this study, we found that a large share of respondents had reassessed their technology needs, or adopted new technologies in response to the Covid-19 crisis. Again, there were differences across groups, but it is interesting to note that across groups the share that adopted new technologies was around 60%, which is consistent with the findings in Riom and Valero (2020) on a wider sample of businesses across the UK.

Figure 13: Firm technology response to Covid-19



Notes: Summary of Covid-19 technology response, by group. Answers to two questions reported: "Has the COVID-19 crisis made you re-assess the technological needs of your business?"; and "Have you adopted any new technologies in response to COVID-19?"

5.2. Analysis of outcomes based on inspection of firm websites

In the absence of a full set of endline data, we inspect company websites to ascertain whether any observable AI technologies have been adopted – most obviously, a chatbot will be visible on a website. This allows us to try to get a second measure of PO3, the binary variable which measures whether firms actually adopted, in the case of chatbots only (other forms of marketing automation are unlikely to be observable in this way).

The inspection consisted of a single visit to company websites, providing a snapshot of a particular point in time for all cohorts (i.e. each website was accessed once in February 2021, which represents at least one year after programme enrolment/baseline). We therefore were not able to observe applications that were no longer active, and note that other tools may have been implemented since. By "chatbots" we considered chat functions that relied on machine learning algorithms, providing targeted, real-time answers to a query (e.g. through keyword recognition, such as "venue address", "opening times", "bookings/reservations"), instead of relying on human interaction (e.g. response from a customer relations analyst). We inspected and assessed each available application carefully, trying to identify to the best of our ability the presence of an AI technology.

Of the 229 firms, 14 were considered closed based on their status on Companies House (e.g. "dissolved", "active proposal to strike off", "liquidation") or their website activity (e.g. website is expired or inactive for a very long period, or contained a message confirming closure). Of the remaining 215 firms, only 2 firms actually adopted a chatbot as previously defined, one having participated in T1 and the other in the control group. Of these two firms, one filled the endline survey, and stated that it had adopted an AI technology (PO3).

Another 34 had a basic chat function/messenger tool on their website that did not rely on AI/machine learning algorithms to provide targeted answers to a query. While we checked websites for chatbots at baseline, we did not record the presence of messengers at that point and, therefore, we are not able assess whether the programme might have influenced the adoption of this non-AI tool.

5.3. Qualitative interviews

The low number of firms interviewed raises issues of internal and external validity, as non-observable characteristics (e.g. motivation) of those that took the time to speak with our evaluation team may be different, on average, from those that did not. Notwithstanding these caveats, some common themes emerged from the qualitative interviews, which help triangulate our quantitative results and provide valuable feedback for future SME technology support programmes. We have organised insights under five key themes that emerged from the discussions.

Theme 1: Technological upgrading and support from government was considered to be beneficial

All firms seemed to agree with the importance of keeping up to date with modern technologies, such as AI, and that these tools could help improve their business performance. Each cited one or more business areas that could benefit from a technological upgrade, including customer experience and retention, social media marketing, target market intelligence, and process optimisation.

"One of the things you quite quickly learn as a small business owner is that (…) you got to adopt a mentality of ongoing lifelong learning. You cannot ever stop. As a small business, you have got to be open to new ideas and new things."

"I am interested in AI, because I want to modernise the way I run the business, it is my personal interest. I was really looking for something that could help me develop some knowledge in this area."

None of the interviewees seemed to have hesitated to apply to the programme. On the contrary, they appeared to be genuinely interested in the opportunity, taking the time to talk about it with industry peers and share news about programme participation with their network through online platforms, such as LinkedIn and blogs. Some interviewees expressed their disappointment with the low attendance in the events.

One interviewee, in particular, expressed the view that, by incentivising the adoption of AI tools, government-led initiatives such as the "Grow with AI" programme could help to tackle the UK's long-standing productivity issue. Indeed, it seemed clear to them what the main objective of the programme was, and the reasons why government was offering this support.

"I appreciate that the government is trying to support us to adopt technologies and make this country a technological hub."

"If government wants to do something about the UK's PLC productivity, (...) [if they want] British industry and commerce to become more competitive and productive, they have got to start talking about the SME sector."

Despite their ex-ante interest and view on the importance of AI technologies to their business, they emphasised the numerous barriers that prevent SMEs from widespread adoption.

Theme 2: Financial constraints were considered to be the main barrier to AI adoption.

Consistent with data from the baseline survey, the financial cost of adoption was highlighted as the main barrier. This was specially emphasised by interviewees that were in the T1 and the control groups, who said that they would have appreciated if some funding had also been made available. This favours the hypothesis that, on average, information alone may not be sufficient to push firms to move along the stages of technology adoption.

"Let us say, for example, that I had attended the event. I could have met a couple of interesting AI providers who would have been able to contribute to the business platform that I have got. However, there would still need to be funding available [to help me implement the technology]."

"In order to encourage adoption, price is key (...). [Support] could come in the form of grants or subsidies."

Although the only interviewee from T2 did not take up the voucher, this was attributed to the Covid-19 pandemic, and it was highlighted that it would have been of great help. In general, this interviewee gave the most positive feedback and, unlike the others, said that the programme had met his initial expectations.

Other issues related to financial constraints were raised, in particular the perception that SMEs act as "price-takers", being unable to negotiate price due to the low competition amongst technology providers. This was also identified as key 'supplier' barrier in the Be the Business report on technology adoption (BTB, 2020). They argue that most technology providers are indeed global and headquartered elsewhere, which can lead to a low customer service and customisation for SMEs.

Theme 3: Information and time constraints were also highlighted as major barriers to AI adoption.

Despite the financial barrier being the most stressed in the interviews, information and time constraints were also cited. In particular, interviewees pointed to the fact that AI is still highly misunderstood, and often thought to be only applicable to larger companies. This, in turn, affects their willingness to devote time and resources to adopting these technologies (including, for instance, searching for products and providers) and adapt their business operation (such as reallocating staff or training them on the new tools).

"It was only after I attended the event that it made me realise that my perceptions of AI are probably very similar to most people's, in that we have got this concept of AI as some kind of super robots, or super computers, which is obviously just not the case."

Interestingly, and perhaps as anticipated, the two interviewees that were assigned to T1 drew attention to the fact that their technology background and personal interest in AI were pivotal to their enrolment and more proactive participation in the programme. In their opinion, if it had not been for this, the information provided in T1 would have done very little to incentivise adoption. This is also in line with the literature, which finds that employee openness to technology is the biggest predictor of implementation success (BTB, 2020).

The interviewees considered that some of the discussion in the events was perhaps too theoretical and broad, without sufficient emphasis on implementation challenges or sector specificity. Similarly, the "Guide for AI" did not seem to make an impression, and was considered insufficient according to the interviewee assigned to the control group (we note that the intention was for the guide to provide only minimal information, as a baseline for all participants in the study).

"Somebody who does not have a technical or technology background may struggle to understand what the relevant theories are, or how they can be helped (...). They may want to see the technology in practice to say 'this is something that I can do'. So there are a lot of things that a programme should be able to bear in mind when you are trying to convince people to adopt an application."

Nevertheless, the information provided seemed to have raised awareness, at least to some extent. For instance, one of the interviewees from T1 decided to adopt a chatbot after coming across a provider that was featured in CX's website following the attendance in the event. Furthermore, as a consequence of the new tool, the interviewee also claimed to have started to pay more attention to other chat functions, including Facebook Messenger and WhatsApp.

The interviewee from the T2 group welcomed the one-on-one meeting with the case worker, and found his recommendations and the more targeted information provided very useful.

Theme 4: Technologies were not considered to be as "shovel-ready" as anticipated.

One issue raised by interviewees was that AI technologies are not yet tools with a 100% efficacy rate. In other words, they still require some degree of human supervision and attention to address failures, which require time. For instance, one interviewee noted that a social media marketing tool with 10% failure rate (e.g. advertisement is sent out to the wrong target group) would require 30% of working hours to fix. Likewise, many of these technologies require employee training, or the need to hire a specialist, such as a software developer. As a consequence, many tasks that had the potential to be automated are still performed manually.

"Once you have done the manual process, it is done. You do not have to check, you are not questioning 'did this application automated what it was supposed to automate?', 'has it fed the data properly?', 'has it displayed the content properly?'. (...) You need to be honest about the efficacy rate because nothing is 100% failproof."

Furthermore, SMEs do not seem to be fully informed about what providers and products are available in the market, and how these can be applied to their business in the most efficient way.

These business-specific implementation costs and failure rates are arguably only observed upon adoption of AI technologies. This would also suggest that consultants providing support to

SMEs might not be able to know with 100% accuracy whether the SMEs can benefit from different technologies, and the exact time and resources that would be needed to transition to these technologies.

Theme 5: Covid-19 was an impediment to greater participant involvement, forcing participants to divert attention from the programme.

Whilst there is broader evidence that Covid-19 has accelerated the adoption of digital technologies (e.g. Riom and Valero, 2020), interviewees underlined that the disruptions caused by the pandemic side-tracked their attention from this specific programme, as they had to restructure and quickly adapt to the shock. As a consequence, they did not seem as willing to devote time into learning about AI providers and adopting their technologies, or adjusting business processes in response. As mentioned, in the case of the interviewee from T2, this also meant not taking up the voucher, even though the meeting with the caseworker was considered to be very helpful.

"It was really difficult to get anything done this year, to get anything productive done. So I just used it as a planning year, trying to get everything organised and in the right place, so we can then reboot."

Firms that already had a strong online presence before the pandemic seemed to have been less adversely impacted by it. Similarly, the effects of Brexit were felt differently depending on the sector and markets in which they operate, with no clear impacts of the trade shock on technology adoption.

5.4. Feedback from implementation partners

In this section, we summarise some of the feedback received from our implementation partners CX and CE on the running of the programme.

Encouraging take-up

As we have set up, both CX and CE found it difficult to achieve high rates of programme take-up. A number of factors appeared to be at play here. First, there were issues with regard to the quality of contact information, which meant that, in some cases, the implementation partners were unable to make contact. This could be due to the fact that companies were signed up over the phone, and in certain cases errors were made as data were input into the baseline survey/application form. There were also issues relating to the fact that businesses received e-mails or contact from a number of different organisations – Integral Research (on behalf of the programme partners), the GLA, and CX or CE, and the LSE team (chasing the endline surveys and inquiring about qualitative interviews). This would have led to confusion, and also increased the chances of e-mails going to junk folders or being missed.

Second, in many cases, once contact had been made, companies did not have a good understanding of what they had signed up for. CX document a mixture of expectations among participants: while some had good knowledge of what they were going to get out of the programme, which appears to be the case of the participants we interviewed, others did not know what to expect. Indeed, the method of recruitment is likely to have influenced the type of firms that signed up to the programme and hence take-up. While some may have had a genuine interest in the support offered, others might have been just curious.

Third, many of the companies that were interested in the programme found it hard to commit time to it. For instance, some that had signed up then failed to show up for workshops or caseworker meetings due to events out of their control, such as childcare issues, problems with business or staff shortages. Given the lack of time, particularly in smaller businesses or solo entrepreneurs, moving events online offered greater flexibility.

The following improvements to the recruitment and delivery processes could help address some of these issues:

- The recruitment process could be refined to better capture participant information. Indeed, part of the eligibility checks could include a confirmation process, whereby companies are sent an e-mail or text for them to confirm their details are correct before the application is officially accepted.
- The programme pitch could be made clearer, so that companies understand what they are signing up for, what they may be offered, and what the potential benefits of participation are. It was challenging to achieve this via the "cold-calling" recruitment method, and perhaps offering these types of programmes to existing (and engaged) members of relevant business networks would help ensure a better understanding. A trailer, or some sort of video content about the programme, could help improve understanding.
- The treatment could also potentially benefit from splitting up groups between firms with pre-existing knowledge and interest in technology adoption, and those that are simply curious. Indeed, a good amount of businesses appear more interested in learning how to run their website properly before including a chatbot on it.
- How the business support in offer is framed, or "sold", could also make a difference when it comes to catching the attention of potentially more motivated firms. For instance, the programme could be sold as a valuable product which the government is temporarily providing a 100% discount for, instead of an experiment that needs voluntary firms to help inform future policymaking.
- Communications could be clearer (and perhaps lead to higher participant engagement throughout the duration of the programme) if all correspondence was coming from one place (e.g. a project management officer e-mail), instead of the multiple stakeholders.

Programme offer

T1 in particular faced issues due to the move to the cohort model. The in-person event that was initially planned to take place at the CogX festival was of a larger scale, and was anticipated to attract a number of vendors to showcase different applications of AI of relevance for retail and hospitality SMEs. Moving to smaller-scale events, it was harder to attract vendors to give up time for such a small audience. The result was one vendor presentation in each of the three interventions, and the vendors were different each time.

In the case of T2, no vouchers were claimed and, from that perspective, a key part of the offer in T2 was not taken up at all. CE considered that addressing the information barrier was insufficient to encourage adoption, and the key constraints for the businesses they had contact with were lack of time or the abilities to implement chatbots or marketing automation technologies. Perhaps the process of using and claiming vouchers contributed to this. Businesses would need to subscribe to an eligible technology, and then claim the cost (up to £750) back from the GLA. CE found that this process was unclear, and this made it difficult to promote the vouchers. Further to this, the time limits on the vouchers evolved with the extension of the trial timelines, which could have caused confusion, though interested T2 SMEs were in touch with the caseworker and aware that they were eligible for the voucher. Feedback from CE suggests that the time limit on the voucher was not necessarily perceived as an additional constraint on firms, rather the ambiguity of what the voucher could be redeemed for was in their view a larger barrier.

The following improvements to implementation could make the programme more effective and easier for firms to participate in:

- The interventions themselves could rely more on technology. Since the pandemic, online meetings and learning have become widespread. Delivering technology support online and providing a recording of the events offers more flexibility, which is important given time constraints faced by business owners.
- More of the support could be automated, from enrolment to treatment delivery, in the spirit of "practicing what we preach". This would allow participants to familiarise themselves with the technology provided and minimise the time required from implementation partners. For example, in the case of the targeted support in T2, applications could be triaged into various stages of technology readiness through a stage-gate process, making use of chatbots to provide advice. Rather than all the business support being "in-person", different media could be employed, including videos, return on investment calculators, and the possibility to book online consultations.
- With relevance for T1, SMEs that have adopted relevant AI technologies could be invited as speakers to events to increase engagement with firms on practical lessons learned. More information on participating firms could be provided to vendors ahead of the events (such as sector, size, or customer target) to ensure that vendor presentations are tailored to participants and their expectations are better met.
- With relevance for T2, the steps involved in claiming the money back through the voucher scheme could be made clearer from the onset. For example, a dedicated guide or a short video on voucher use could be sent to firms. However, it is possible that the reclaim method itself is a barrier to adoption. It could help if the end vendor takes the liability for the sales process instead through procurement laws.

Covid-19

A number of businesses closed down during this period. In addition, disruption and uncertainty due to the pandemic is likely to have diverted attention from the AI technologies that were the subject of this study, with businesses prioritising the immediate changes required to adjust their operations – including the adoption of more basic digital technologies, such as a new website or online sales. CX also reported difficulties to contact the third cohort during lockdown, since many of the contact numbers provided were store numbers, which could have been shut.

6. Conclusions

6.1. Effectiveness of the evaluation

Two issues limit the effectiveness of the evaluation. Any conclusions drawn from our quantitative data must be heavily caveated due to a lack of power as a result of the high level of attrition we experienced. In addition, attrition appears to be non-random between treatment groups on some dimensions, which threatens initial randomisation. As ever, even if attrition had been balanced on observables, we might worry about imbalance on unobserved factors. We therefore focus on a descriptive rather than causal analysis of the results, and caveat the statistical analyses provided in the appendix, offering tentative hypotheses that might explain our results.

The main threats to external validity were the large macro-economic shocks (Brexit and Covid-19) that hit UK SMEs, particularly in London's retail and hospitality sectors, during our trial. Uncertainty due to Brexit might have held back investments. From March 2020, the Covid-19 crisis was particularly disruptive for businesses in the retail and hospitality sectors – causing many businesses to shut down temporarily or to adopt new technologies in order to adapt to changed consumption and work patterns. We asked questions in our endline to understand the extent to which the pandemic might have affected outcomes.

While we have been unable to provide a robust evaluation of this randomised control trial, we have generated quantitative and qualitative data that can help inform future programmes of technology support.

6.2. Effectiveness of the programme

Large recruitment problems were apparent before the pandemic and were further heightened by the Covid-19 crisis. At a high level, we can conclude that the trouble we had recruiting participants and the low take-up suggests that the support offered by this programme, and the way in which it was delivered, did not address the priorities of our sample of businesses, pre- or post-pandemic. Indeed, this is corroborated by the qualitative interviews: participants from T1 and the control group felt that the information provided did not focus on the day-to-day practicalities and challenges associated with the adoption of these technologies, being too theoretical at times and not targeted enough. The lack of financial support was also emphasised. On the other hand, the participant interviewed from T2 welcomed the one-to-one meeting provided by the case worker, as well as the financial assistance from the voucher, which would have been put to use if not for the disruptions caused by the pandemic.

While we are unable to generate robust estimates of treatment effects in this study, on the 43 endline observations we have, it appears that adoption-related activity (in particular allocating resource towards exploring the adoption of AI technologies) in the treatment groups was higher than in the control group – though there was no discernible difference in terms of actual adoption of chatbots and marketing automation. However, attitudes/intentions regarding AI technologies appear to be more positive in the control group. Looking at the changes in the attitudes questions, all groups reported a better understanding of the costs and benefits of AI technologies, but also lower scores on the attitudes questions relating to perceived benefits to the business, and whether decision-making would be influenced by other firms in the sector. Indeed, in Appendix Table A8, we see that even when controlling for attitudes at baseline, the coefficients for treated firms (relative to the control group) are negative across the attitudes questions (though not significant). However, this is an intention to treat analysis, and it appears that the negative changes in attitudes are driven mainly by firms that did not participate in the treatments. Sample sizes are too small to estimate on-treatment effects.

Our data have helped to shed light on the barriers to AI adoption faced by retail and hospitality SMEs showing that, in line with other surveys on broader technologies and with wider sectoral/geographic coverage, the top three ranked barriers relate to financing constraints (the costs of new software and reorganisation) and skills. Information and time barriers were also emphatically underlined during the interviews. As we intended in the programme design, we found quantitative and qualitative evidence that firms in the T2 group, who received a more targeted intervention, considered that the programme addressed barriers to a greater extent than firms in T1.

Our results suggest that the trial might have led to both positive and negative unanticipated effects. All firms in the endline survey claim to have sought out external advice, primarily on general use digital/IT technologies. While this was likely to have been induced by Covid-19, being part of the trial might have increased awareness on technology adoption amongst the sample. However, firms in our endline survey also updated their beliefs downwards about the potential positive impacts that they anticipate AI technologies having on their businesses. For instance, the SMEs we interviewed seemed to find that technologies were not as "shovel-ready" as anticipated. Arguably the trial might have dissuaded some firms to adopt AI technologies, and might have instead incentivised firms to take action on their technology needs in different ways.

However, our qualitative evidence suggests that SMEs understand the importance of technological upgrading to their business performance, and seem willing to adopt these tools as long as they prove to be cost-effective. They also appeared to understand why programmes such as the "Growth with AI" are potentially relevant for the UK economy more broadly. Interviewees appreciated the government's effort to provide business support, and hoped that this would continue in the future.

6.3. Lessons learned and implications for policy

A key lesson we have learned is that future programmes of business support targeted at small businesses in retail and hospitality (or similar) sectors, and associated trial designs, should take active steps to anticipate that managers have limited time, and that despite the self-selection into the trial, are likely to struggle to attend interventions, albeit free and beneficial for their business. More flexibility in the provision of support, including remote provision, is likely to be beneficial for this target audience.

The most successful method of recruitment, direct phone marketing, was resource-intensive, and also led to the recruitment of businesses that did not necessarily have an effective understanding of the programme offer. Moreover, there were issues with respect to the quality of contact information, and confusion as participants were contacted by a number of organisations involved in the trial. It might be preferrable to establish one point of contact for all communication with firms, confirm contact details upon acceptance into the programme, and build more flexibility and automation into the interventions themselves.

We find weak evidence of demand for the types of AI technologies we offered in the trial among SMEs in the retail and hospitality sectors. It may be preferrable to seek out more evidence of the demand for these technologies within the target demographic prior to an RCT. Respondents reported that the trial addressed many barriers to technology adoption and improved their understanding of these technologies. While overall attitudes in the treatment groups became less positive towards AI, this appears to be driven by SMEs that did not participate in the treatments. We have found evidence that firms in these sectors are interested in technology adoption and in receiving technology advice. Indeed, all firms in our endline sample had sought external advice on technology adoption, though much of this appears to have been prompted by the pandemic.

Our experience on this programme helped inform the design of the new Technology Adoption Service on the London Business Hub, launched in March 2021. This free service is built as a searchable online platform and marketplace of technology providers to signpost small businesses to the best fit technology solutions for their needs. Drawing on lessons learned in this programme, the platform is more focused on tried-and-tested technologies – such as web-based accounting, cloud-based computing, e-commerce and customer relationship management systems – rather than the more cutting-edge solutions that were the subject of this trial.

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Appendix 1: Appendix Tables and Figures

Appendix Table A1: Baseline balance- key characteristics and outcomes at baseline

Variable	(1) T1	(2) T2	(3) C	(4) T1C diff (pval)	(5) T2C diff (pval)	(6) T2T1 diff (pval)
Stratum- Retail	0.63	0.62	0.62	0.013 (0.868)	0.005 (0.950)	-0.008 (0.917)
Stratum- Small	0.63	0.62	0.62	0.013 (0.868)	0.005 (0.950)	-0.008 (0.917)
Manager- male	0.64	0.63	0.63	0.013 (0.867)	0.000 (1.000)	-0.013 (0.867)
Manager- degree	0.61	0.65	0.71	-0.105 (0.174)	-0.061 (0.421)	0.044 (0.576)
Manager- young	0.51	0.43	0.53	-0.020 (0.811)	-0.092 (0.259)	-0.072 (0.376)
Firm- Employees (#)	14.41 [24.17]	15.14 [31.12]	19.18 [46.21]	-4.776 (0.426)	-4.041 (0.526)	0.735 (0.871)
Firm- Employment has grown	0.45	0.38	0.45	0.000 (1.000)	-0.071 (0.377)	-0.071 (0.377)
Firm- Employment growth ambition	0.87	0.87	0.82	0.053 (0.377)	0.054 (0.359)	0.002 (0.975)
Firm- Revenue (£000)	190.08 [541.24]	138.07 [248.71]	128.03 [234.04]	62.054 (0.392)	10.040 (0.805)	-52.015 (0.454)
Firm- Revenue has grown	0.66	0.6	0.62	0.039 (0.615)	-0.021 (0.792)	-0.060 (0.442)
Firm- Revenue growth ambition	0.91	0.99	0.91	0.000 (1.000)	0.079** (0.028)	0.079** (0.028)
Firm- More productive than competitors	0.3	0.26	0.34	-0.039 (0.605)	-0.082 (0.270)	-0.043 (0.558)
Firm- Competition considered fierce	0.66	0.7	0.7	-0.039 (0.605)	0.004 (0.958)	0.043 (0.568)
Firm- Strong digital capabilities	0.24	0.31	0.18	0.053 (0.429)	0.127* (0.069)	0.075 (0.303)
Firm- Strong marketing capabilities	0.17	0.17	0.26	-0.092 (0.171)	-0.094 (0.158)	-0.002 (0.971)
Firm- conducted CBA on AI tech	0.12	0.06	0.14	-0.026 (0.634)	-0.080 (0.108)	-0.053 (0.254)
Firm- competitors use AI tech	0.25	0.22	0.33	-0.079 (0.286)	-0.108 (0.136)	-0.029 (0.673)
Barrier- info on tech	2.08 [0.83]	2.3 [0.78]	1.95 [0.73]	0.132 (0.300)	0.351*** (0.005)	0.220* (0.093)
Barrier- info on tech providers	2 [0.8]	2.17 [0.83]	2.04 [0.7]	-0.039 (0.747)	0.129 (0.301)	0.169 (0.203)
Barrier- management/workforce skill	2.04 [0.76]	2.23 [0.78]	2.17 [0.79]	-0.132 (0.296)	0.063 (0.621)	0.194 (0.119)
Barrier- applicability to business	2.08 [0.78]	2.05 [0.83]	1.96 [0.76]	0.118 (0.343)	0.091 (0.476)	-0.027 (0.836)
Barrier- resistence to change, managers	1.41 [0.64]	1.48 [0.7]	1.36 [0.58]	0.053 (0.595)	0.125 (0.231)	0.073 (0.503)
Barrier- resistance to change, staff	1.39 [0.59]	1.45 [0.64]	1.38 [0.59]	0.013 (0.891)	0.073 (0.464)	0.060 (0.549)
Barrier- financing constraints	2.39 [0.75]	2.36 [0.76]	2.32 [0.79]	0.079 (0.528)	0.048 (0.702)	-0.031 (0.799)
Barrier- reorganisation costs	2.14 [0.74]	2.31 [0.8]	2.13 [0.82]	0.013 (0.918)	0.180 (0.171)	0.167 (0.183)
Barrier- uncertainty in tech market	1.93 [0.77]	2.09 [0.76]	1.96 [0.79]	-0.026 (0.836)	0.130 (0.301)	0.157 (0.209)
Barrier- uncertainty on customer impact	1.96 [0.76]	1.97 [0.73]	1.82 [0.81]	0.145 (0.257)	0.158 (0.205)	0.013 (0.910)
Barrier- uncertainty over demand in sector	1.97 [0.75]	1.75 [0.73]	1.78 [0.78]	0.197 (0.113)	-0.023 (0.850)	-0.220* (0.067)
Barrier- macro uncertainty	2.03 [0.82]	1.97 [0.81]	1.86 [0.86]	0.171 (0.210)	0.119 (0.381)	-0.052 (0.691)
PO1- resource allocated to exploring AI	0.2	0.16	0.21	-0.013 (0.842)	-0.055 (0.385)	-0.042 (0.504)
PO2- how likely to adopt AI (1-5)	2.96 [1.23]	3.08 [1.24]	3.14 [1.39]	-0.184 (0.388)	-0.067 (0.755)	0.117 (0.558)
SO1- attitudes, good understanding of AI (1-5)	2.08 [1.3]	2 [1.11]	2.07 [1.15]	0.013 (0.947)	-0.066 (0.719)	-0.079 (0.687)
SO1- attitudes, AI leads to increased revenues (1-5)	3.3 [1.17]	3.22 [1.08]	3.38 [1.11]	-0.079 (0.669)	-0.161 (0.365)	-0.082 (0.654)
SO1- attitudes, AI leads to increased profits (1-5)	3.28 [1.15]	3.36 [1.01]	3.25 [1.11]	0.026 (0.886)	0.114 (0.509)	0.087 (0.619)
SO1- attitudes, AI leads to increased customers (1-5)	3.34 [1.17]	3.49 [1.06]	3.41 [1.15]	-0.066 (0.727)	0.086 (0.632)	0.151 (0.403)
SO1- attitudes, AI has positive impact on business (1-5)	3.34 [1.14]	3.52 [1.05]	3.45 [1.26]	-0.105 (0.589)	0.072 (0.700)	0.177 (0.317)
SO1- attitudes, AI influenced by others in sector (1-5)	2.7 [1.25]	2.77 [1.3]	2.53 [1.13]	0.171 (0.378)	0.240 (0.224)	0.069 (0.739)
SO3- Introduced new tech/practices in last 6m	0.38	0.32	0.38	0.000 (1.000)	-0.057 (0.465)	-0.057 (0.465)
Number of observations	76	77	76	153	152	153

Notes: The sample is 229 firms surveyed at baseline. T1 refers to Treatment 1, T2 to Treatment 2 and C to control group. Note that the following variables have some missing values; manager male and manager young dummy, and revenue. Employment or Revenue growth ambition are dummies=1 answered that they would want to see their business slightly or significantly larger than its current size on each measure respectively (Q29 and Q31, baseline). In the firm-related variables, competition considered fierce is a dummy=1 if companies consider themselves to face intense of very intense competition (Q35, baseline) or that if they were to go out of business, competitors would take up all of their sales (Q37, baseline). Companies were considered to have strong digital or marketing capabilities when they rated themselves 4 or 5 out of 5 (Q42, 43, baseline). Standard deviations of continuous variables reported in columns 1-3 in square brackets. Differences in means and p values reported in columns 4-6. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively

Appendix Table A2: Summary of take-up and endline survey completion by cohort

	Group	Take-up	# Firms	Endline
Cohort 1	C	N	20	6
	T1	Y	7	1
	T1	N	14	2
	T2	Y	12	4
	T2	N	9	3
Cohort 1	C	N	29	7
	T1	Y	9	1
	T1	N	19	2
	T2	Y	12	3
	T2	N	16	3
Cohort 3	C	N	27	3
	T1	Y	2	0
	T1	N	25	5
	T2	Y	10	2
	T2	N	18	1
All	**C**	**N**	**76**	**16**
	T1	**Y**	**18**	**2**
	T1	**N**	**58**	**9**
	T2	**Y**	**34**	**9**
	T2	**N**	**43**	**7**
	Totals:		**229**	**43**

Notes: Take-up is defined as attending the programme event in the T1 group, and either attending the event or attending/booking a one-to-one in the T2 group. No control group firms had access to the treatments as they were by invitation only.

Appendix Table A3: Detailed summary of take-up by cohort

	Cohort 1		Cohort 2		Cohort 3		Total	
	T1	T2	T1	T2	T1	T2	T1	T2
(1) Allocated	21	21	28	28	27	28	76	77
(2) Signed up initially	9	13	13	9	7	11	29	33
(3) Declined, but interested	5	2	4	2	6	0	15	4
(4) Signed up, but no show	2	2	4	1	5	2	11	5
(5) No commit	0	0	0	3	0	2	0	5
(6) Declined	3	5	0	7	2	1	5	13
(7) No reply	4	0	11	3	12	13	27	16
(8) Attended event	7	10	9	6	2	9	18	25
(9) Booked one-to-one	0	3	0	1	0	1	0	5
(10) Attended one-to-one	0	7	0	11	0	3	0	21
(11) Take-up, (8)|(9)|(10)	7	12	9	12	2	10	18	34
Take-up % (11)/(1)	**33%**	**57%**	**32%**	**43%**	**7%**	**36%**	**24%**	**44%**
(12) Engaged, (3)+(4)	7	4	8	3	11	2	26	9
Engaged % (12)/(1)	**33%**	**19%**	**29%**	**11%**	**41%**	**7%**	**34%**	**12%**

Notes: Categories of take-up and engagement provided by the implementation partners.

Appendix Table A4: Comparison of baseline characteristics by uptake

Panel A: Treatment groups separately

	Treatment 1			Treatment 2		
Variable	**Participated**	**Dropped-out**	**p-val**	**Participated**	**Dropped-out**	**p-val**
Stratum- Retail	0.83	0.57	(0.043)	0.65	0.60	(0.707)
Stratum- Small	0.67	0.62	(0.728)	0.76	0.51	(0.023)
Manager- male	0.67	0.64	(0.827)	0.50	0.74	(0.033)
Manager- degree	0.61	0.60	(0.954)	0.79	0.53	(0.018)
Manager- young	0.50	0.51	(0.949)	0.33	0.51	(0.123)
Firm- Employees (#)	7.44	16.57	(0.163)	18.62	12.40	(0.387)
Firm- Employment has grown	0.39	0.47	(0.574)	0.41	0.35	(0.577)
Firm- Employment growth ambition	0.89	0.86	(0.772)	0.91	0.84	(0.340)
Firm- Revenue (£000)	376.03	124.23	(0.100)	144.79	132.91	(0.838)
Firm- Revenue has grown	0.72	0.64	(0.517)	0.71	0.51	(0.086)
Firm- Revenue growth ambition	0.94	0.90	(0.546)	1.00	0.98	(0.377)
Firm- More productive than competitors	0.33	0.29	(0.750)	0.29	0.23	(0.547)
Firm- Competition considered fierce	0.83	0.60	(0.074)	0.62	0.77	(0.158)
Firm- Strong digital capabilities	0.33	0.21	(0.276)	0.35	0.28	(0.494)
Firm- Strong marketing capabilities	0.17	0.17	(0.956)	0.24	0.12	(0.171)
Firm- conducted CBA on AI tech	0.11	0.12	(0.914)	0.09	0.05	(0.467)
Firm- competitors use AI tech	0.39	0.21	(0.122)	0.15	0.28	(0.170)
Barrier- info on tech	2.33	2.00	(0.137)	2.21	2.37	(0.356)
Barrier- info on tech providers	2.33	1.90	(0.042)	2.21	2.14	(0.731)
Barrier- management/workforce skill	2.33	1.95	(0.059)	2.26	2.21	(0.758)
Barrier- applicability to business	2.28	2.02	(0.217)	2.03	2.07	(0.833)
Barrier- resistence to change, managers	1.39	1.41	(0.886)	1.29	1.63	(0.037)
Barrier- resistance to change, staff	1.39	1.40	(0.962)	1.26	1.60	(0.020)
Barrier- financing constraints	2.56	2.34	(0.301)	2.32	2.40	(0.683)
Barrier- reorganisation costs	2.22	2.12	(0.616)	2.32	2.30	(0.909)
Barrier- uncertainty in tech market	2.00	1.91	(0.682)	2.06	2.12	(0.746)
Barrier- uncertainty on customer impact	2.11	1.91	(0.337)	2.06	1.91	(0.365)
Barrier- uncertainty over demand in sector	1.94	1.98	(0.851)	1.85	1.67	(0.288)
Barrier- macro uncertainty	1.89	2.07	(0.417)	1.82	2.09	(0.149)
PO1- resource allocated to exploring AI	0.33	0.16	(0.100)	0.15	0.16	(0.853)
PO2- how likely to adopt AI (1-5)	3.83	2.69	(0.000)	3.00	3.14	(0.628)
SO1- attitudes, good understanding of AI (1-5)	2.33	2.00	(0.347)	1.94	2.05	(0.683)
SO1- attitudes, AI leads to increased revenues (1-5)	3.72	3.17	(0.081)	3.18	3.26	(0.752)
SO1- attitudes, AI leads to increased profits (1-5)	3.56	3.19	(0.241)	3.44	3.30	(0.553)
SO1- attitudes, AI leads to increased customers (1-5)	3.78	3.21	(0.071)	3.50	3.49	(0.962)
SO1- attitudes, AI has positive impact on business (1-5)	3.72	3.22	(0.105)	3.59	3.47	(0.611)
SO1- attitudes, AI influenced by others in sector (1-5)	2.50	2.76	(0.449)	2.68	2.84	(0.592)
SO3- Introduced new tech/practices in last 6m	0.44	0.36	(0.536)	0.35	0.30	(0.643)

Notes: The sample is 76 T1 firms and 77 T2 firms for all variables except the following that have some missing values: manager male and manager young dummy, and revenue. For derived firm variable descriptions see Appendix Table A1.

Panel B: Treatment groups pooled

Variable	Participated	T1 and T2 Dropped-out	p-val
Stratum- Retail	0.71	0.58	(0.124)
Stratum- Small	0.73	0.57	(0.058)
Manager- male	0.56	0.68	(0.138)
Manager- degree	0.73	0.57	(0.058)
Manager- young	0.39	0.51	(0.172)
Firm- Employees (#)	14.75	14.79	(0.993)
Firm- Employment has grown	0.40	0.42	(0.887)
Firm- Employment growth ambition	0.90	0.85	(0.366)
Firm- Revenue (£000)	223.41	128.33	(0.188)
Firm- Revenue has grown	0.71	0.58	(0.124)
Firm- Revenue growth ambition	0.98	0.93	(0.190)
Firm- More productive than competitors	0.31	0.27	(0.602)
Firm- Competition considered fierce	0.69	0.67	(0.813)
Firm- Strong digital capabilities	0.35	0.24	(0.156)
Firm- Strong marketing capabilities	0.21	0.15	(0.329)
Firm- conducted CBA on AI tech	0.10	0.09	(0.887)
Firm- competitors use AI tech	0.23	0.24	(0.925)
Barrier- info on tech	2.25	2.16	(0.509)
Barrier- info on tech providers	2.25	2.00	(0.074)
Barrier- management/workforce skill	2.29	2.06	(0.081)
Barrier- applicability to business	2.12	2.04	(0.581)
Barrier- resistence to change, managers	1.33	1.50	(0.119)
Barrier- resistance to change, staff	1.31	1.49	(0.091)
Barrier- financing constraints	2.40	2.37	(0.771)
Barrier- reorganisation costs	2.29	2.20	(0.495)
Barrier- uncertainty in tech market	2.04	2.00	(0.771)
Barrier- uncertainty on customer impact	2.08	1.91	(0.189)
Barrier- uncertainty over demand in sector	1.88	1.85	(0.795)
Barrier- macro uncertainty	1.85	2.08	(0.092)
PO1- resource allocated to exploring AI	0.21	0.16	(0.418)
PO2- how likely to adopt AI (1-5)	3.29	2.88	(0.053)
SO1- attitudes, good understanding of AI (1-5)	2.08	2.02	(0.783)
SO1- attitudes, AI leads to increased revenues (1-5)	3.37	3.21	(0.413)
SO1- attitudes, AI leads to increased profits (1-5)	3.48	3.24	(0.188)
SO1- attitudes, AI leads to increased customers (1-5)	3.60	3.33	(0.158)
SO1- attitudes, AI has positive impact on business (1-5)	3.63	3.33	(0.099)
SO1- attitudes, AI influenced by others in sector (1-5)	2.62	2.79	(0.418)
SO3- Introduced new tech/practices in last 6m	0.38	0.34	(0.559)

Notes: The sample is 153 firms (76 T1 firms and 77 T2 firms pooled together) for all variables except the following that have some missing values: manager male and manager young dummy, and revenue. For derived firm variable descriptions see Appendix Table A1.

Appendix Table A5: Is attrition related to treatment status?

Dependent variable: Attrition	T1C	T2C	T2T1
T1	0.0681		
	(0.062)		
T2		0.00295	-0.0642
		(0.065)	(0.062)
Cohort 2	0.0560	0.0952	0.0854
	(0.084)	(0.093)	(0.084)
Cohort 3	0.0839	0.221**	0.100
	(0.086)	(0.087)	(0.086)
Retail (stratum)	-0.0509	-0.0597	-0.0296
	(0.070)	(0.073)	(0.071)
Small (stratum)	-0.0717	-0.0130	-0.0518
	(0.066)	(0.071)	(0.067)
Observations	152	153	153

Notes: Robust standard errors in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. Tests for survey attrition as specified in the PAP.

Appendix Table A6: Comparison of baseline characteristics of non-attritors to attritors

Variable	Full sample: Non-Attritors	Attritors	p-val
Stratum- Retail	0.67	0.61	(0.455)
Stratum- Small	0.70	0.61	(0.273)
Manager- male	0.49	0.67	(0.026)
Manager- degree	0.79	0.62	(0.038)
Manager- young	0.40	0.51	(0.174)
Firm- Employees (#)	12.74	17.05	(0.468)
Firm- Employment has grown	0.53	0.40	(0.102)
Firm- Employment growth ambition	0.86	0.85	(0.856)
Firm- Revenue (£000)	100.28	164.33	(0.303)
Firm- Revenue has grown	0.58	0.63	(0.520)
Firm- Revenue growth ambition	0.95	0.93	(0.578)
Firm- More productive than competitors	0.37	0.28	(0.264)
Firm- Competition considered fierce	0.72	0.68	(0.582)
Firm- Strong digital capabilities	0.35	0.22	(0.078)
Firm- Strong marketing capabilities	0.26	0.19	(0.321)
Firm- conducted CBA on AI tech	0.12	0.11	(0.869)
Firm- competitors use AI tech	0.28	0.26	(0.835)
Barrier- info on tech	2.19	2.09	(0.480)
Barrier- info on tech providers	2.28	2.02	(0.051)
Barrier- management/workforce skill	2.21	2.13	(0.569)
Barrier- applicability to business	1.84	2.08	(0.073)
Barrier- resistence to change, managers	1.28	1.45	(0.123)
Barrier- resistance to change, staff	1.23	1.45	(0.032)
Barrier- financing constraints	2.44	2.34	(0.425)
Barrier- reorganisation costs	2.21	2.19	(0.906)
Barrier- uncertainty in tech market	2.02	1.99	(0.796)
Barrier- uncertainty on customer impact	2.02	1.89	(0.313)
Barrier- uncertainty over demand in sector	1.86	1.83	(0.800)
Barrier- macro uncertainty	2.00	1.94	(0.674)
PO1- resource allocated to exploring AI	0.16	0.19	(0.643)
PO2- how likely to adopt AI (1-5)	3.00	3.08	(0.730)
SO1- attitudes, good understanding of AI (1-5)	2.16	2.02	(0.482)
SO1- attitudes, AI leads to increased revenues (1-5)	3.42	3.27	(0.446)
SO1- attitudes, AI leads to increased profits (1-5)	3.47	3.26	(0.262)
SO1- attitudes, AI leads to increased customers (1-5)	3.63	3.37	(0.168)
SO1- attitudes, AI has positive impact on business (1-5)	3.74	3.37	(0.051)
SO1- attitudes, AI influenced by others in sector (1-5)	3.00	2.59	(0.046)
SO3- Introduced new tech/practices in last 6m	0.35	0.37	(0.838)

Notes: The sample is 229 firms for all variables except the following that have some missing values: manager male and manager young dummy, and revenue. In outcomes variables, AI relates to chatbots and marketing automation technologies. For derived firm variable descriptions see Appendix Table A1.

Appendix Table A7: Balance on non-attriting sample

	Sample means			p-values		
Variable	**T1**	**T2**	**C**	**T1C**	**T2C**	**T2T1**
Stratum- Retail	0.73	0.63	0.69	(0.832)	(0.721)	(0.597)
Stratum- Small	0.82	0.63	0.69	(0.466)	(0.721)	(0.298)
Manager- male	0.45	0.56	0.44	(0.933)	(0.495)	(0.598)
Manager- degree	0.82	0.75	0.81	(0.972)	(0.681)	(0.689)
Manager- young	0.64	0.38	0.25	(0.047)	(0.462)	(0.196)
Firm- Employees (#)	10.00	17.63	9.75	(0.969)	(0.316)	(0.443)
Firm- Employment has grown	0.55	0.75	0.31	(0.242)	(0.012)	(0.286)
Firm- Employment growth ambition	0.82	0.94	0.81	(0.972)	(0.300)	(0.351)
Firm- Revenue (£000)	150.70	97.16	68.74	(0.483)	(0.544)	(0.661)
Firm- Revenue has grown	0.55	0.75	0.44	(0.598)	(0.076)	(0.286)
Firm- Revenue growth ambition	1.00	1.00	0.88	(0.239)	(0.154)	(.)
Firm- More productive than competitors	0.36	0.31	0.44	(0.714)	(0.481)	(0.792)
Firm- Competition considered fierce	0.73	0.75	0.69	(0.832)	(0.705)	(0.900)
Firm- Strong digital capabilities	0.36	0.44	0.25	(0.543)	(0.279)	(0.714)
Firm- Strong marketing capabilities	0.18	0.25	0.31	(0.466)	(0.705)	(0.689)
Firm- conducted CBA on AI tech	0.36	0.00	0.06	(0.050)	(0.325)	(0.007)
Firm- competitors use AI tech	0.36	0.19	0.31	(0.792)	(0.431)	(0.323)
Barrier- info on tech	2.09	2.13	2.31	(0.515)	(0.533)	(0.924)
Barrier- info on tech providers	2.18	2.19	2.44	(0.416)	(0.373)	(0.987)
Barrier- management/workforce skill	2.00	2.13	2.44	(0.174)	(0.284)	(0.691)
Barrier- applicability to business	1.73	2.00	1.75	(0.948)	(0.405)	(0.422)
Barrier- resistence to change, managers	1.00	1.38	1.38	(0.021)	(1.000)	(0.057)
Barrier- resistance to change, staff	1.00	1.25	1.38	(0.057)	(0.518)	(0.077)
Barrier- financing constraints	2.64	2.25	2.50	(0.627)	(0.381)	(0.223)
Barrier- reorganisation costs	1.91	2.25	2.38	(0.133)	(0.674)	(0.286)
Barrier- uncertainty in tech market	1.91	2.06	2.06	(0.664)	(1.000)	(0.647)
Barrier- uncertainty on customer impact	1.91	2.13	2.00	(0.792)	(0.649)	(0.446)
Barrier- uncertainty over demand in sector	2.09	1.69	1.88	(0.568)	(0.533)	(0.214)
Barrier- macro uncertainty	2.18	1.88	2.00	(0.605)	(0.681)	(0.357)
PO1- resource allocated to exploring AI	0.27	0.19	0.06	(0.141)	(0.300)	(0.617)
PO2- how likely to adopt AI (1-5)	2.91	2.81	3.25	(0.551)	(0.370)	(0.849)
SO1- attitudes, good understanding of AI (1-5)	2.73	2.13	1.81	(0.086)	(0.414)	(0.235)
SO1- attitudes, AI leads to increased revenues (1-5)	3.45	3.06	3.75	(0.480)	(0.053)	(0.397)
SO1- attitudes, AI leads to increased profits (1-5)	3.55	3.13	3.75	(0.611)	(0.081)	(0.383)
SO1- attitudes, AI leads to increased customers (1-5)	3.45	3.31	4.06	(0.153)	(0.020)	(0.752)
SO1- attitudes, AI has positive impact on business (1-5)	3.55	3.56	4.06	(0.237)	(0.116)	(0.964)
SO1- attitudes, AI influenced by others in sector (1-5)	2.73	2.81	3.38	(0.234)	(0.246)	(0.890)
SO3- Introduced new tech/practices in last 6m	0.45	0.31	0.31	(0.472)	(1.000)	(0.472)
Observations	11	16	16	27	32	27

Notes: In outcomes variables, AI relates to chatbots and marketing automation technologies. For derived firm variable descriptions see Appendix Table A1.

Appendix Table A8: ITT Regressions

Panel A: T1 versus C

		Basic ITT			Baseline outcomes		
		T1	s.e.	Obs	T1	s.e.	Obs
(1)	PO1- Resource allocated to exploring AI	0.215	(0.156)	27	0.128	(0.147)	27
(2)	PO2- How likely to adopt AI (1-5)	0.0843	(0.587)	27	0.0959	(0.602)	27
(3)	PO3- Adopted AI	0.0140	(0.156)	27			
(4)	SO1- attitudes, good understanding of AI	0.439	(0.592)	27	-0.226	(0.479)	27
(5)	SO1- attitudes, increased revenues	-0.670	(0.420)	27	-0.482	(0.408)	27
(6)	SO1- attitudes, increased profits	-0.575	(0.455)	27	-0.415	(0.356)	27
(7)	SO1- attitudes, increased customers	-0.890**	(0.412)	27	-0.529	(0.422)	27
(8)	SO1- attitudes, positive business impact	-0.765	(0.492)	27	-0.418	(0.411)	27
(9)	SO1- attitudes, influenced by other firms	-0.774	(0.597)	27	-0.268	(0.392)	27
(10)	SO2- Adoption more likely	-0.00681	(0.181)	23			
(11)	SO3- Introduced new broader tech last 6m	0.0272	(0.199)	27	0.00122	(0.217)	27
(12)	Adoption Index (mean PO1,PO3,SO2,SO3)	0.0599	(0.120)	27			
(13)	Attitudes Index (mean SO1,PO2)	-0.450	(0.372)	27			

Panel B: T2 versus C

		Basic ITT			Baseline outcomes		
		T2	s.e.	Obs	T2	s.e.	Obs
(1)	PO1- Resource allocated to exploring AI	0.149	(0.143)	32	0.0777	(0.132)	32
(2)	PO2- How likely to adopt AI (1-5)	-0.680	(0.451)	32	-0.632	(0.457)	32
(3)	PO3- Adopted AI	-0.0223	(0.137)	32			
(4)	SO1- attitudes, good understanding of AI	-0.249	(0.537)	32	-0.372	(0.488)	32
(5)	SO1- attitudes, increased revenues	-0.341	(0.481)	32	-0.168	(0.536)	32
(6)	SO1- attitudes, increased profits	-0.502	(0.440)	32	-0.181	(0.467)	32
(7)	SO1- attitudes, increased customers	-0.558	(0.437)	32	-0.183	(0.466)	32
(8)	SO1- attitudes, positive business impact	-0.638	(0.441)	32	-0.493	(0.464)	32
(9)	SO1- attitudes, influenced by other firms	-0.554	(0.471)	32	-0.226	(0.384)	32
(10)	SO2- Adoption more likely	0.315*	(0.153)	29			
(11)	SO3- Introduced new broader tech last 6m	0.0410	(0.176)	32	0.0417	(0.179)	32
(12)	Adoption Index (mean PO1,PO3,SO2,SO3)	0.120	(0.093)	32			
(13)	Attitudes Index (mean SO1,PO2)	-0.503	(0.346)	32			

Panel C: T2 versus T1

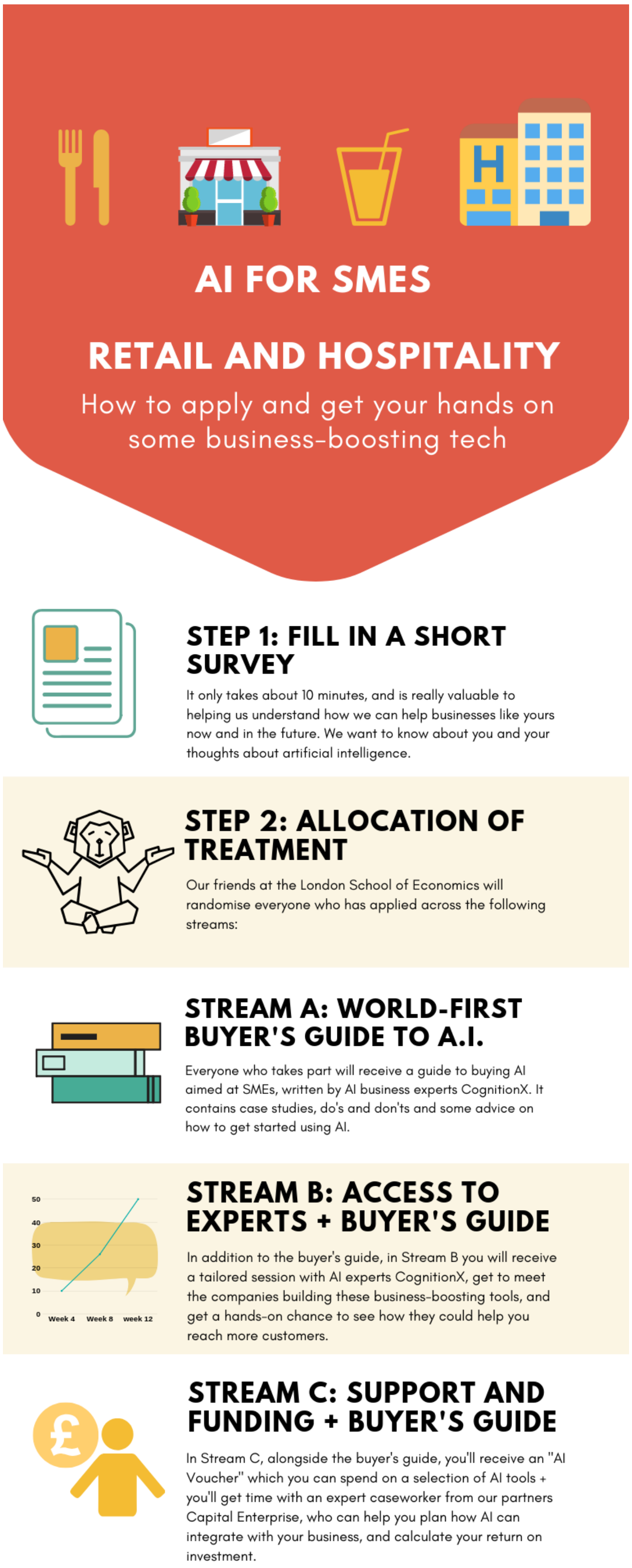
		Basic ITT			Baseline outcomes		
		T1	s.e.	Obs	T1	s.e.	Obs
(1)	PO1- Resource allocated to exploring AI	-0.0705	(0.224)	27	0.00897	(0.180)	27
(2)	PO2- How likely to adopt AI (1-5)	-0.543	(0.588)	27	-0.281	(0.435)	27
(3)	PO3- Adopted AI	0.00125	(0.143)	27			
(4)	SO1- attitudes, good understanding of AI	-0.407	(0.709)	27	-0.133	(0.591)	27
(5)	SO1- attitudes, increased revenues	0.252	(0.470)	27	0.440	(0.332)	27
(6)	SO1- attitudes, increased profits	0.00484	(0.564)	27	0.267	(0.448)	27
(7)	SO1- attitudes, increased customers	0.269	(0.494)	27	0.369	(0.389)	27
(8)	SO1- attitudes, positive business impact	0.127	(0.607)	27	0.178	(0.449)	27
(9)	SO1- attitudes, influenced by other firms	0.473	(0.483)	27	0.378	(0.445)	27
(10)	SO2- Adoption more likely	0.292	(0.198)	24			
(11)	SO3- Introduced new broader tech last 6m	-0.0722	(0.198)	27	-0.0276	(0.225)	27
(12)	Adoption Index (mean PO1,PO3,SO2,SO3)	0.0376	(0.128)	27			
(13)	Attitudes Index (mean SO1,PO2)	0.0252	(0.453)	27			

Panel D: T1T2 versus C – Pooled regressions

	Basic ITT			Baseline outcomes		
	T1T2	s.e.	Obs	T1T2	s.e.	Obs
(1) PO1- Resource allocated to exploring AI	0.183	(0.128)	43	0.0893	(0.113)	43
(2) PO2- How likely to adopt AI (1-5)	-0.342	(0.449)	43	-0.253	(0.458)	43
(3) PO3- Adopted AI	-0.00223	(0.122)	43			
(4) SO1- attitudes, good understanding of AI	0.0176	(0.495)	43	-0.311	(0.425)	43
(5) SO1- attitudes, increased revenues	-0.388	(0.431)	43	-0.130	(0.443)	43
(6) SO1- attitudes, increased profits	-0.471	(0.410)	43	-0.203	(0.376)	43
(7) SO1- attitudes, increased customers	-0.617	(0.405)	43	-0.204	(0.396)	43
(8) SO1- attitudes, positive business impact	-0.628	(0.408)	43	-0.330	(0.405)	43
(9) SO1- attitudes, influenced by other firms	-0.605	(0.447)	43	-0.252	(0.315)	43
(10) SO2- Adoption more likely	0.209	(0.143)	38			
(11) SO3- Introduced new broader tech last 6m	0.0607	(0.155)	43	0.0519	(0.160)	43
(12) Adoption Index (mean PO1,PO3,SO2,SO3)	0.112	(0.093)	43			
(13) Attitudes Index (mean SO1,PO2)	-0.433	(0.326)	43			

Notes: Robust standard errors in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. Each panel relates to the comparison specified. In Panel D, T1T2 is a dummy which equals one if the firm was in either treatment group. Basic ITT specifications are as set out in equation (1), i.e. In each row, the outcome specified is regressed on cohort and stratum dummies. “Baseline outcomes” specifications are as Basic ITT, but also control for the outcome at baseline (where it was asked). Where the specified outcomes were not asked at baseline no result is reported (similarly for the indices, since not all constituent questions were asked at baseline).

Appendix Figure A1: Overview of trial from GLA programme initial web-page (later re-branded as Grow with AI in communications)



Appendix 2: Power calculations

This appendix updates the analysis set out in our Pre-Analysis Plan (Valero, 2019) for the sample size we actually achieved at endline.

Background

Due to recruitment challenges and high attrition, the trial sample size is lower than initially anticipated. In our initial trial protocol we aimed for a total of N=400, with T1=100, T2=100 and C=200. This was determined by our desire to have a sufficient sample to detect reasonable differences between the treatment and control groups, as set out in the protocol, but subject to budget constraints – the main one being the funds required, such that each T2 firm could claim a voucher in the programme. We updated the protocol for a new cohort design in light of recruitment difficulties and specified that while we would still aim for N=400 across the cohorts, having an excess of recruits to put in the control group seemed overly optimistic. Therefore, we specified that we would use an equal allocation ratio – i.e. in each cohort we would split the recruited SMEs equally into T1, T2 and C.

Across all cohorts we recruited 229 firms into the study. Here we set out basic power calculations for the two primary outcomes on which we had data at baseline, based on three scenarios

- A benchmark scenario of all 229 firms filling out the endline survey (at around 75 firms in each arm, there would be around 150 observations in a regression that compares T1 and C, or T2 and C) – this was set out in the PAP.
- An intermediate scenario where just half (114) of firms filled out the endline survey (at around 38 firms in each arm, there would be around 76 firms in a regression that compares T1 and C, or T2 and C).
- ***Update to the PAP***: The final sample of 43 firms that filled out the endline survey (with 16 firms in T2, 11 in T1, and 16 in C) – we calculate the minimum detectible effects assuming that we have 30 observations in each regression that compares two arms.

In our PAP, we noted that given low uptake of the interventions, we would primarily be testing ITT.

Due to our low sample size, our planned focus was on the comparison of Treatment 1 and Control, and of Treatment 2 and Control. We considered that we would be unlikely to have enough power to detect a significant difference between T2 and T1.

<u>Primary Outcome 1 (PO1) - binary, with baseline data</u>

Technology assessment process

Binary variable 0,1: Answer to “Have you allocated staff time or resource to exploring the possible adoption of chatbots / marketing automation technologies?”

This variable can be analysed both as a level at endline and as a change from baseline, and will give us information on whether firms are committing resources to moving forwards within the persuasion stage.

According to the baseline data from the three cohorts, 19% of the sample reported “1” on this variable. The following power calculations assume that this is unchanged at endline for the control group.

Table AI. Power Calculations for PO1 – Treatment 1/Treatment 2 and Control

Scenario	Benchmark	50% Attrition	Final Sample
Total Sample size	229	114	43
Sample for T1/C or T2/C regression	150	76	30
Arm size	75	38	15
Minimum Detectible Effect (MDE)	21%	30%	49%

Note. Point estimates are rounded to integer. Statistical power of 80% and statistical significance of 95%.

<u>Primary Outcome 2 (PO2)– non-binary, with baseline data</u>

Intentions to adopt chatbots/marketing automation technologies

Continuous variable: Answer to “how likely are you to adopt chatbots/marketing automation technologies over the next 12 months?” score 1-5, 1=very unlikely, 5=very likely.

This variable can be analysed both as a level at endline and as a change from baseline, and will give us information on whether firms are moving from persuasion towards decision.

According to the data from the three cohorts at baseline, we assume the control group’s intention to adopt is 3.06 (standard deviation of 1), which we round up to 3 for our power calculations. Note – this analysis also applies for the secondary outcomes on attitudes to AI (SO1), for which the scaling and baseline descriptives are similar.

Table AII. Power Calculations for PO2– Treatment 1/Treatment 2 and Control

Scenario	Benchmark	50% attrition	Final sample
Total Sample size	229	114	43
Sample for T1/C or T2/C regression	150	76	30
Arm size	75	38	15
Minimum Detectible Effect (MDE)	0.46	0.65	1.06

Note. Point estimates are rounded to integer. Statistical power of 80% and statistical significance of 95%.

In the benchmark scenario, the Minimum Detectible Effect is roughly half of a standard deviation. In the scenario with 50% attrition, the MDE increases to 0.65 of a standard deviation and in our final sample to 1.06 standard deviations. As a rule of thumb, half a standard deviation is considered a large effect.

Ex-post discussion of the impact of attrition on power calculations

In the benchmark scenario,[26] power calculations show that for the trial to be able to detect a significant effect, the share of treated firms that would have had to allocate resources to explore adoption (PO1) needed to be at least 21% higher than the share in the control group. This would require 16 (out of 75) more firms allocating resources in the treated group compared to the control group. In our Pre-Analysis Plan (Valero, 2019) we flagged that this large effect might be difficult to achieve.

The ensuing 81% attrition across the sample further reduced our ability to detect significant effects. In our final scenario for outcome PO1 (column 3 of Table AI), the minimum detectable effect more than doubles compared to baseline (from 21% to 49%). In this scenario where the treatment arm size is 15, given 3 firms had adopted in the control group, 10 out of the 15 T1 or T2 firms would have had to allocate resources to explore AI for us to conclude that the effect of the trial was statistically significant.

This is considerably larger than the outcomes observed in our endline survey and explains the lack of statistical significance in our ITT results. Indeed, in Figure 5 we show that 19% of firms in the control group reported having allocated time and resources to exploring the possible adoption of technologies, compared to 36% and 38% of T1 and T2 firms respectively. Furthermore, the treatment arms are not equal in our endline survey. Focusing on T2 and the control group (both made up of 16 firms), the 19% difference in PO1 observed is far lower than the 49% difference we would need to detect significance in our final sample. In other words, given that 3 firms reported allocating resources in the control group, we would have needed 11 firms out of 16 to allocate resources in T2 to detect significance, rather than 6 firms – roughly twice more.

Similarly for PO2, we would have needed a difference of 1.06 points (out of 5 points) between T1 or T2 firms and the control group to detect significance. In contrast, comparing again control groups firms with T2 firms, we find that control groups firms in fact rate their likelihood of adoption to be 0.56 points higher than T2 firms. This result is not in the direction we would have anticipated and is about half the impact we would have needed to detect a significant difference.

[26] Total of 229 firms and assuming equal treatment arms at endline (of 75 firms)

Appendix 3: Summary of recruitment and endline chasing – direct approach

Recruitment

The following summarises recruitment efforts across the 3 cohorts.

In Cohort 1 we initially attempted to recruit participants via outreach (via email and social media) from the GLA and related networks. We then trialled a more direct approach, hiring *Integral Research* (IR) to call businesses based on a sample of eligible businesses which they accessed. We found this to be the most effective method, and transitioned to this as our main model (though we continued social media communications and other routes in later cohorts).

Script for direct outreach

IR were provided with a briefing from the evaluation team, and a script to guide telephone conversations, as follows. Detailed information about the trial was available on the GLA webpage, to which potential applications were directed.

I am [name] calling from [institution].

I am calling to draw your attention to a government-funded programme we are delivering with the Greater London Authority to support companies like yours through providing funding and information on how advanced technologies can help you grow your business.

You should have received an email last week from the London Growth Hub – an organisation funded by the Mayor of London and Central Government.

We have already received applications from companies like yours, and we want to encourage you to sign up. There are still spaces left on the programme, and just by answering a survey which should take you 12 minutes or so, you will be entered into the programme.

On the programme you could receive access to part of a £200,000 pot of support, and trial technologies that could:

- *Provide visitors to your [type of business] with tailored, personalised recommendations;*
- *Give you the power of a 24/7 marking department;*
- *Showcase your products with new customers on social media;*
- *Optimise your bookings and make more money with less;*

All participants will receive a world first guide to AI technology aimed at SMES.

Applications close on the [cohort closing date], so please go to www.growthhub.london/technology today (please note the double 'h' in the middle there)

Recruiting data

The data on efforts made by IR were provided to us by the team manager.

Cohort 1 – 62 signed up in total, 19 by IR

2,445 business contacted, and a total of 3,987 calls made, with an average call attempt of 1.6 per sample loaded.

Average calls made to each signed up business: 3.2

Cohort 2 – 85 signed up in total, 78 by IR

2,725 business contacted, and a total of 9,455 calls made, with an average call attempt of 3.5 per sample loaded.

Average calls made to each signed up business: 4.1

Cohort 3 – 82 signed up in total, 78 by IR

3,137 business contacted, and a total of 14,182 calls made, with an average call attempt of 4.5 per sample loaded.

Average calls made to each signed up business: 5

Endline chasing

The GLA sent emails to all businesses that had signed up to the programme, with links to the endline survey, and these were followed up by reminders. Complete rates were very low, so we decided to employ IR to help with chasing endline surveys. But due to data sharing restrictions, they were only able to contact the businesses that they had originally signed up to the programme. The LSE team therefore chased the businesses that had been recruited by other means – this was mainly an issue in Cohort 1. The following is a summary on endline chasing efforts, provided to the evaluation team by IR:

Cohort 1: IR received a list of 19 companies to follow up on and achieved 5 completes. Average number of call attempts was 13 but that increased to an average of 16 call attempts for records that were "live" (not terminated as completes or dead).

Cohort 2: IR received 78 companies to follow up on and achieved 19 completes. Average number of call attempts was 15 but that increased to an average of 21 call attempts for records that were "live" (not terminated as completes or dead). On final outreach, IR could not reach anyone by phone, so sent the email with the self-complete survey link as a last attempt.

Cohort 3: IR received 78 companies to follow up on and achieved 10 completes. Average number of call attempts is 13 but that increased to an average of 19 call attempts for records that were "live" (not terminated as completes or dead). This was a challenging cohort as it coincided with further restrictions due to COVID-19. On final outreach, IR could not reach anyone by phone, so sent the email with the self-complete survey link as a last attempt.

Below is the status breakdown.

Row Labels	Cohort 1	Cohort 2	Cohort 3	Grand Total
Reached voicemail and left message	3			3
Completed	5	19	10	34
No reply	8		6	14
No Such Person	1	3	1	5
Refusal	1	9	10	20
Refusal - Quit during Interview	1	1		2

Refusal at Gateway		1	2	3
Terminated (Company inactive / Closed)		2	1	3
Transfer to Web (sent survey link by email)		41	46	87
Unobtainable		2	2	4
Grand Total	**19**	**78**	**78**	**175**

Following completion of IR's work, the LSE team sent personal e-mails as a last attempt to encourage SMEs to fill the endline survey. This did not yield any additional survey completes.

Other appendices provided in separate files

Appendix 4: Survey Instrument – Baseline

Appendix 5: Survey Instrument – Endline

Appendix 6: Discussion Guide for Interviews

Appendix 7: Provided separately – Data and Syntax

Appendix 8: AEA Registry Documents are available here:

https://www.socialscienceregistry.org/trials/3999

Appendix 9: Guide to AI