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# Technology Adoption and Skills
# A Pilot Study of Kent SMEs

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**Abstract**

Does the successful deployment of digital technologies require complementary investment in skills? We conducted a pilot survey to investigate. The survey elicited information on whether the firm was adopting one of the three digital technologies of interest (AI, robotics, big data), provided in-house training, and whether they experienced any problems recruiting workers. We find evidence that new technologies require complementary skill investments and that firms deem both new technologies and training of their workforce important for productivity. While there is some heterogeneity across the type of technologies (Robotics, AI, Big Data) introduced, firms facing difficulties attracting workers with the right skills are more likely to run own training programmes. This might suggest that there is a skills gap that may be holding back productivity and economic growth. Overall, the findings from our pilot survey demonstrate firms' awareness of the need for skills to complement new technologies to realise the productivity benefits in full.

**Keywords:** capital-skill complementarity; business performance; technology adoption
**JEL codes:** J24, M53, O33

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## 1. Introduction

Digital technologies have revolutionised firms and jobs but the benefits in terms of improved economic performance have been slower to materialise. Unlike previous general-purpose technologies that have improved efficiency in production by speeding up existing processes using less resources, the growth of artificial intelligence (AI), robotics and the use of big data are changing how businesses function and the way production takes place from their innovation and design processes to their use of raw materials and managing their supply chain. Such whole-scale developments have been slower to manifest in measurable productivity improvements and certainly the UK continues to suffer with low levels of productivity growth, compared to other nations.

That productivity growth has been slow despite the advent of new technologies may be due to the need for complementary skills or because of firms' inability to incorporate this latest wave of technology into their existing models and platforms. If this is the case, existing data on productivity and firm behaviour is falling short on asking the right questions to help economists and policy makers understand exactly what it is that is preventing productivity gains materialising from the latest wave of technology and may in part explain some elements of the productivity puzzle. To shed light on this, we have designed a survey which explores firms' engagement with the latest wave of digital technology, AI, Robotics and Big Data, as well as challenges they face with complementary skills required to successfully utilise them.

While skills shortages are common at times of rapid technology adoption (Boothby et al, 2010), the warning signs for digital skills shortage have been evident for the past decade. In the 2014 Small Business Survey - a national survey of UK SMEs - a quarter of SMEs reported not having basic digital skills[1] (BMG Research and Durham University, 2015), despite there being a positive correlation between digital skills and turnover growth. More recent research by the Industrial Strategy Council (2019) estimates that around 7 million workers will be under-skilled for their jobs by 2030, which represents 20% of the UK labour force. It is therefore vital to better understand the nexus of technological change and relevant skills.

Through our survey, we investigate whether the successful deployment of digital technologies requires complementary investment in appropriate labour in order to reap the productivity benefits. Our questionnaire is largely based on a survey used in Japan, following the work of Morikawi (2017; 2020). The pilot survey draws on FAME as a sample for Kent SMEs and produced around 42 valid firm-level responses, operating across a range of production and service sectors. Specifically, the survey elicited information on whether the firm was adopting one of the three digital technologies of interest (AI, robotics, big data) and if they experienced any problems recruiting workers. The survey also sought information on the extent to which organisations provided in-house training, implicitly to see whether firms were investing in their workforce to address skills gaps they had identified through recruitment challenges.

While the uptake in the pilot survey was low, there are a number of interesting findings. While not all firms surveyed were adopting digital technologies, many saw the potential benefits. Similarly, most firms deemed training of their workforce important for productivity. Of those surveyed, 28.6% often experienced difficulties in recruiting the right person for the

[1] Digital skills have be defined by JISC as comprising of information, data and media literacies; digital creation, problem solving and innovation; ICT proficiency; digital learning and development.

job, with a further 47.6% sometimes experiencing difficulties. There is suggestive evidence that new technologies require complementary skill investments. Of those indicating that they felt technology was both important and currently performed in their workplace to enhance productivity, over 90% already engaged with enhancing employee education and training. Our results further suggest that hiring employees with the relevant skills for new technologies or training existing employees are strategic substitutes, as firms facing difficulties attracting workers with the right skills are more likely to run own training programmes. This might suggest that there is a skills gap that may be holding back productivity and economic growth. Overall, the findings from this pilot survey demonstrate that SMEs' awareness of the need for skills to complement new technologies to realise the productivity benefits in full.

This paper is structured as follows: we undertake a review of the literature which summarises the existing evidence and studies of relevance to the area of human capital and successful technology adoption. This provides a backdrop for our anticipated findings in relation to the variables of interest, which informs the survey design. In section 4, we provide details of the surveying approach adopted, outlining the population and sampling frame as well as providing initial details regarding the initial survey. Our findings are then presented in section 5 and then finally, in section 6 we draw conclusions from our pilot survey of SMEs in Kent, reflecting on the findings of our survey and suggest directions for future research.

## 2. Existing evidence on skills adoption and technology

It is well understood that productivity improvements and the accumulation of human capital are fundamental drivers of economic growth and prosperity. While historically technologies and workers' skills were mostly studied separately, recent literature has argued that there are important complementarities between the two. Bartel et al (2007) for instance document using detailed US longitudinal data at the plant level for one industry, valve manufacturing, that the adoption of new IT production technologies coincides with increased skill requirements as well as with the adoption of new human resource practices. Their results suggest that to harvest the full potential of new technologies investments in the workforce are needed.

Conversely, Brynjolfsson and McElheran (2016) in their study of the adoption of data-driven decision-making technologies find that complementarities matter for technology choice, with firms with better educated workers being more likely to adopt the new technology. However, in an analysis of Spanish manufacturing firms, Koch, et al (2021) find that firms that are more skill-intensive ex ante are less likely to introduce robots than less skill-intensive firms. The difference across these two papers suggests that no universal patterns can be draw, but that the relationship between human capital and technology adoption might depend institutional settings that differ across countries or on the nature of new technologies. In fact, there is a recent literature that argues that the effects of technological change are heterogeneous across tasks, and thus across workers' occupations, and across industrial sectors (see for example Acemoglu and Restrepo (2019) and Bárány and Siegel (2021)).

These are some of the reasons why we think it is important to conduct an analysis for the UK, in order to improve our understanding of UK firms' technology and human capital choices and constraints. In our pilot survey on UK firms, we do not focus on one single technology, but a wider set, and gather multiple indicators on workers' skill requirements and training investments. We follow closely the work of Morikawa (2017, 2020) who has collected such survey data on Japanese firms. Where possible or in our view applicable to the UK context, we follow his survey's questions on technology and complementary skills. The results in

Morikawa (2017) show that in Japan firms with a better educated workforce tend to benefit more from AI technologies. Morikawa (2020) shows that digital technologies, such as AI and big data, are positively associated with employees' educational attainment, whereas there is no relationship between the use of industrial robots and workers' skill measures in the manufacturing sector. Again, this demonstrates the heterogeneity of the relationship between technologies and workers' skills and the necessity to study UK firms.

Our study is also motivated by Brynjolfsson et al (2021) who observe that general purpose technologies (GPTs), such as AI, both enable and require significant complementary investments, spanning from direct investment into human capital to the development of new processes, products, and business models. Yet, as Brynjolfsson et al. (2021) point out, these complementary investments are often of an intangible nature and therefore not well captured in national accounts, and this typically leads to understating productivity when new technologies appear. An alternative explanation is that the complementary investments lag the technological and so productivity gains are slow to emerge. This paper seeks to explore these two potential explanations for a small sample of Kent Small to Medium sized Enterprises.

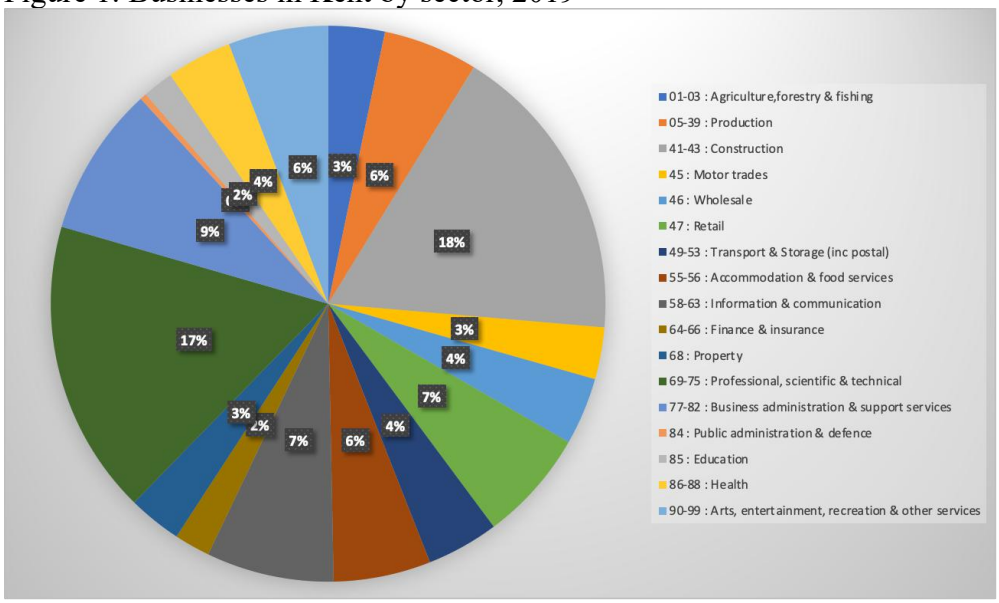
## 3. The SME landscape in Kent

As a pilot study, we have deliberately focussed on small and medium sized enterprises, defined as those organisations that have 250 or less employees located in Kent. The narrow definition of our population enables us to assume some degree of commonality regarding conditions and institutional factors faced by organisations. We know that Europe is characterised as being comprised of primarily SMEs, who account for around two thirds of employment and 55% of value added (Tankler, 2020), and therefore, focussing on SMEs offers a representative business entity.

Our population of businesses is identified using Financial Analysis Made Easy (FAME) – an online database constructed by Bureau van Djik, which collates information gathered and stored as part of national requirements at Company's House. These data are accessible via a paid-for portal, enabling us to gather information on all businesses required by law to publish financial accounts. Thus, in theory, FAME should contain the population of all registered organisations required to make a submission. We know that FAME is not a perfect record, that particularly underrepresents smaller sized enterprises. Ideally, the IDBR – the Interdepartmental Business Register - would be used as the standard frame from which to draw our sample. This register is however held by the ONS and is anonymised at any point of access available to academic researchers which prevents primary data collection from these enterprises. However, FAME has been used in several previous productivity studies (Fouskas and Robinson, 2019; Faggio et al, 2010).

By way of background, we firstly present general evidence of Kent Businesses below. Around 72,000 businesses are reported to exist in Kent and Medway, 90% of businesses employ less than 10 workers (Matthews et al, 2021). Matthews et al (2021) also report that job density in Kent sits at 0.77 – ie 0.77 jobs per working age person – which is lower than the UK average (of 0.87) Figure 1 shows in which sectors businesses in Kent are based. Many two-digit sectors are represented but Kent is dominated by firms in Construction, Professional, Scientific and Technical and Business Administration, together accounting for around 44% of businesses in 2019.

Figure 1: Businesses in Kent by sector, 2019




Source: IDBR 2019

While there is some merit in limiting the reach of the analysis to specific sectors, or firms located in high-tech sectors (manufacturing and services), this does restrict the potential number of responses. Moreover, this is less useful in narrowly defined areas as there is less industrial diversity. In addition, technologies such as AI and robotics are general purpose technologies and by their very nature, transcend sector boundaries. Broadening the sector reach gives the study greater inclusion. Therefore, the study included all firms identified in FAME that had less than 250 employees, were in Kent and in manufacturing or service sectors (thus excluding only primary sectors).

Recent research undertaken by Matthews et al (2021) highlights the extent of skills gaps in Kent and Medway. Their paper identifies national trends such as the growth in digitalisation, the future importance of decarbonisation and the impact this is likely to have on production and skills needs for the future, as well as an aging labour force, there are some clear local trends. These include evidence of growing occupational gaps in management (SOC11 &12) and business, media and public associate professionals (SOC24 &34) as well as a clear structural need for more workers in the caring and personal service occupations. Conversely, there was a decline in workers in areas such as secretarial occupations and other administrative occupations (Figure A, p. ii).

Overall therefore, the Kent Economy is broadly reflective of the national situation, with a few specialisms and areas for specific need.

## 4. The Survey

An exploration of existing data sources found that many firm level surveys undertaken in the UK cover either the innovation process (UK-IS) or skills shortages (ESS) but rarely include detailed questions on both. Matching opportunities exist but are likely to lead to small unrepresentative samples of very large firms. The Small Business Survey provides an alternative but has less detail on the use of specific innovative technologies (BMG Research & Durham University, 2015). Thus, to answer the broad research questions, a new survey was required.

Use of FAME as the source of our sample of businesses in Kent. Ideally would have wanted to use the IDBR as a framework but issues of confidentiality around this as a sample frame meant that we could not have direct access and contact details. FAME in theory is linkable, although the level of the unit of analysis is problematic, but the sample size of the pilot is likely to be too small to make such an activity fruitful. Moreover, FAME contains up to 10 years of financial records on a company. Thus, links to previous financial records are possible.

The survey was conducted remotely using a survey software package[2]. This was particularly important given the Covid-19 situation that has dominated the full duration of the project. Many workers within firms will have been working remotely as far as possible and so those likely to complete the survey were unlikely to have been essential to production aspects of their business. This context may account for the low response rate for the survey but is also worth bearing in mind since it may affect the types of organisations that responded because they were less directly affected by Covid-19 and able to continue in operation.

The survey itself was based around a survey designed to reflect on a similar survey conducted in Japan (Morikawa, 2017; 2020). Specifically, we were interested in understanding technology adoption within firms, around the areas of Artificial Intelligence and Robotics, and the extent to which these caused changes in the skills requirements of the labour force within these firms. We also ask the extent to which firms address skills requirements themselves by offering in-house training provision, or whether they aim to recruit new skilled workers into the organisation. In the case of the latter, we are interested in the extent to which firms observe skills gaps.

One objective of the research was to maximise the value of the data collected and match back into the FAME data, which stores time series of turnover and numbers of employees for approximately 10 years. This would provide us with objective labour productivity proxies. Other variables included in FAME also offer several potential controls should it have been possible to undertake econometric analysis. However, the extent to which this would be possible would be very much dependent on the number of survey responses gained and as a result, we include estimates of relative productivity in our questionnaire. In any case, our survey responses standalone would permit bivariate analysis at the very least.

### 4.1 Data Summary

The survey was conducted using Qualtrics, an online survey tool. Contact details (email address and name of contact) were extracted from FAME and then merged into Qualtrics to create the distribution list. We were able to identify 2,737 FAME records that met our search criteria (active companies, based in Kent, with less than 250 employees). From these, we then extracted email addresses, which left us with 4,702 contacts. Of these, 1,882 were emailed requesting if they could complete the survey themselves or forward on to the most appropriate person in their organisation.

The survey was open from November 2020 to February 2021, with reminder emails sent periodically to those who had not yet responded until February. We were also able to promote the survey through the KBS Kent and Medway Business Summit. The survey period was a period marked by national lockdowns and fluctuating levels of Covid-19 infections which meant that offices were largely unoccupied. An online survey was the best

[2] Following University of Kent Ethical Approval.

approach to use, but we recognise that some businesses are likely to have decided to mothball activities during this period. Indeed, recent work by ONS suggests that survey responses across the board were significantly lower than pre-Covid-19 levels (Merad, 2021). In addition, it was a period of considerable change and uncertainty (because of Brexit) and therefore perhaps not a time conducive to seek responses to a business survey. However, the purpose in this study was to pilot possible survey questions to elicit a better understanding of how firms embed technology within their organisation and the extent to which complementary human capital is (a) available and (b) fit for purpose.

Table 1 provides a summary of responses achieved. We obtained 47 responses, of which 30 matched directly back into FAME which offered some potential to gather information back over time. However, the characteristics of these firms indicate that they are significantly larger than those that could not be matched back in. This is consistent with our understanding that FAME does a much better job of capturing larger firms.

Table 1: Surveyed organisations in Kent

| | Turnover (th. GBP) | Average Number of Employees | Turnover per Employee | Firm Age | observations |
|---|---|---|---|---|---|
| not-matched | 288,106 | 5.2 | 566,933 | 44.3 | 17 |
| matched | 2,860,518 | 8.8 | 2,858,383 | 35.6 | 30 |
| all | 2,088,794 | 8.2 | 2,454,009 | 38.4 | 47 |

Table 2 provides an overview of the dimensions of the data from the survey. Note that our respondents are in organisations that are on average 25 years old, and operate predominantly from one location, although 43% are part of multi-site organisations. A relatively small proportion of organisations have a female managing director. This is low by national (publicly listed) standards but note also that our sample is dominated by founder-led management (55.8%).

Profit and sales are the focus for organisations and long-term growth is the main issue. A third of respondents identified as having one-year business planning in place, with almost a quarter having no planning. Optimism amongst Kent SMEs surveyed appears to be high with almost three quarters forecasting sales growth over the next 5 years, although most respondents forecast between 6 and 25% growth over the 5 years (relatively modest) but with some confidence (50%+ confidence expressed by 88% of respondents). In terms of market reach, the respondents appear to be relatively evenly split in terms of market focus, across the local, national and international levels and it was interesting that almost 60% of respondents placed emphasis on quality in relation to competitive edge. Almost 62% of respondents stated that their organisation had some form of bonus, or performance related remuneration scheme in place. Most respondents said their organisation did not have a recognised union in their workplace.

Table 2: Survey data summary

| ***Organisational Characteristics*** | | ***No responses*** |
|---|---|---|
| Multi-site organisations (Q8) | 43% | 44 |
| Age of firm (median) (Q9) | 25 years | 44 |
| Female-led organisations (Q11) | 14.3% | 42 |
| Modal age of Managing Director (Q12) | 50-59 years (51%) | 43 |
| Founder-led (Q13) | 55.8% | 43 |
| ***Performance and Practice*** | | |
| Main management objective (Q14) | Profit level (41.5%) | 41 |
| | Sales/profit growth (40%) | |
| Main management issue (Q15) | Long term corporate growth (61%) | 41 |
| No Business Plan (Q16) | 23.8% | 41 |
| 1-year business plan (Q16) | 33.3% | |
| Sales forecast for next 5 years (Q17) | Increase (73.8%) | 42 |
| Scale of growth - 6-25% growth (Q18) | 52.8% | 36 |
| Confidence in forecast (Q19) | 88% (>50% confident) | 42 |
| Local market (Q21) | 36% | 42 |
| National market (Q21) | 38% | |
| International market (Q21) | 26% | |
| Competitive focus (Q22) – quality | 59.5% | 42 |
| Competitive focus (Q22) – price | 28.6% | |
| Performance Related Pay in place (Q24) | 62% | 42 |
| Company-paid educational and training programme (Q25) | 70% | 40 |
| Recognised union (Q26) | 7.5% | 40 |

## 5. Findings

Overall, our dataset provides us with a small window of insight into the relationship SMEs in Kent have with the latest wave of technology. This enables us to consider the research questions in relation to incorporation of technology. In the section below we take each in turn and discuss the evidence we have.

*RQ1: What is the uptake of the latest wave of technology in Kent SMEs?*

The questionnaire specifically asks about new workplace practices as well as the use of new technologies. Table 3 shows the percentage of responses for each of the activities (recognising that an organisation may do more than one). We note that technological improvement was the most common form of new activity, followed by the development of new products and services. A small number of respondents indicated they had engaged in no new activities.

Table 3: Q29 "In the past 3 years, has your firm engaged in any of the following new activities?"

| | **%** |
|---|---|
| Entry into new types and forms of business | 50.0 |
| Development of new products and services | 69.0 |
| Technological improvement and upgrading of existing goods and/or services | 81.0 |
| Adoption of new production and distribution methods for goods and/or services | 52.4 |
| None of the above | 7.1 |
| **N of observations** | **43** |

In terms of engagement with international business, 52% of respondents replied that they engaged with either exporting to a new market, establishing an overseas branch or engaged in foreign acquisition. Thus, Kent SMEs included in our sample show a considerable global outlook. When asked individually about their attitude towards Big Data, AI and Robotics,

our respondents indicated different levels of engagement with each. Table 4 summarises this information (Q31-Q33) thus:

Table 4: "What is your firm's attitude towards….."

| | Big Data % | AI % | Robotics % |
|---|---|---|---|
| Already using | 24.3 | 8.3 | 2.8 |
| Planning to use | 16.2 | 22.2 | 11.1 |
| Nothing to do with our business | 35.2 | 36.1 | 52.8 |
| Nothing Specific | 24.3 | 33.3 | 33.3 |
| **N of observations** | **37** | **36** | **36** |

Note that from Table 4 we see robotics as being seen as relatively niche, with the perception in the majority of respondents that it has nothing to do with their line of business. Big data shows the greatest level of uptake, with almost a quarter of businesses already using it. AI sits somewhere in the middle of the spectrum, with a more than a fifth of businesses seeing the potential but less than 10% currently using. Thus, in answer to our first research question, our survey results suggest different levels of uptake across these three components of new technology, but strongest adoption of big data.

*RQ2: Do SMEs identify a productivity gain from technology adoption?*

When asked which of the following factors is thought to contribute to productivity[3] respondents to our survey were provided with a small range of options that included training and the upgrading of machinery and equipment, as well as the expansion or use of new technology. These findings are presented in Table 5. It can be seen that in each instance, the dominant response to most practices is that they are both important and performed, with 50% of respondents engaging in reviews of business process flow and enhanced employee education and training. Considered to be least important was the introduction and replacement of labour saving machinery.

Table 5: Q27 - "Which of the following measures are considered important by your firm to improve productivity and which are currently being performed?"

| | Important (%) | Performed (%) | Important & performed (%) | Neither important nor performed (%) | N |
|---|---|---|---|---|---|
| Introduction/replacement of labour-saving machinery/equipment | 9.8 | 19.5 | 43.9 | 26.8 | **41** |
| Development/expanded use of new technology | 27.5 | 17.5 | 47.5 | 7.5 | **40** |
| Review of business process flow | 14.6 | 19.5 | 51.2 | 14.6 | **41** |
| Rationalisation of employee work styles | 26.2 | 14.3 | 40.5 | 19.1 | **42** |
| Enhancement of employee education/training | 25.0 | 17.5 | 50.0 | 7.5 | **40** |
| Reduction of indirect costs | 27.5 | 20.0 | 45.0 | 7.5 | **40** |
| Shrinkage or elimination of inefficient divisions | 37.5 | 7.5 | 32.5 | 22.5 | **40** |

Overall then, it appears as though technology and training are seen as important components of modern workplace practices in the process of enhancing productivity.

[3] In the survey, we do not offer a definition of productivity although implicit in our discussion is the assumption that the respondent will assume a measure of labour productivity most commonly defined as output or value added per hour worked.

*RQ3: Do SMEs identify a skills gap resulting from technology adoption?*
In our survey, we asked respondents whether they felt that in the long run, technology adoption and diffusion of AI and robotics would have a positive or negative impact on future management and business activities as well as employment within their organisation. By and large, the responses indicate a high degree of uncertainty about how or whether they will be affected in the longer run (about 73% indicating no effect on business and management activities). In terms of the employment, the impact is more evenly distributed, with around 20% of respondents feeling that employment will be negatively affected and over a third (38%) indicating no likely effect. However, around 38% of respondents also felt they did not know how employment would be affected by technology in the longer run.

*RQ4: Do SMEs correct for skills gaps by providing internal training opportunities?*
When asked directly about the likely consequences of AI and robotics with regards to employment and training opportunities, respondents identified most clearly that there would be little or no direct impact on hiring or in-house education, although almost 11% felt more complementary training would be necessary. A small number of respondents felt that there would hiring of AI relevant workers and that lower skilled workers would lose out, but this is not the overwhelming view.

Table 6: In your opinion, has the introduction of AI or robotics resulted in…

| | **%** |
|---|---|
| Introducing complementary training and education to support employees | 10.8 |
| Hiring new workers with AI relevant skills | 8.1 |
| Hiring lower skilled workers to work alongside AI technology | 0.0 |
| Laying off high skilled workers (degree and above) | 0.0 |
| Laying off low skilled workers (GCSE and below) | 8.1 |
| None of the above | 73.0 |
| **N of responses** | **37** |

*Bivariate analysis*
Notwithstanding the limitations of the sample, we are able to make a number of comparisons across variables that sheds light on the interaction between technology introduction and skills gaps. Our results are presented below in a series of figures that offer visual representation of bivariate relationships because we recognise that there are challenges from drawing statistical inference on such a small sample.

Figure 1 captures the extent to which firms engaged both in technologies to improve productivity as well as equipment that is labour saving. We see that around 48% of respondents both valued and engaged with new technology and of this 48%, around 70% also valued and engaged employed labour-saving equipment. The extent to which there is overlap between technology and labour-saving equipment is not formally explored in this study, but an implicit assumption is that new technology is labour saving. At the other end of the spectrum, we see that those who did not engage or value new technology as a means of improving productivity were also those who were less likely to engage with labour saving equipment. Drivers of these differences may of course be sector specific rather than an unwillingness to engage with new technologies.

Figure 1: The introduction of labour-saving equipment to improve productivity

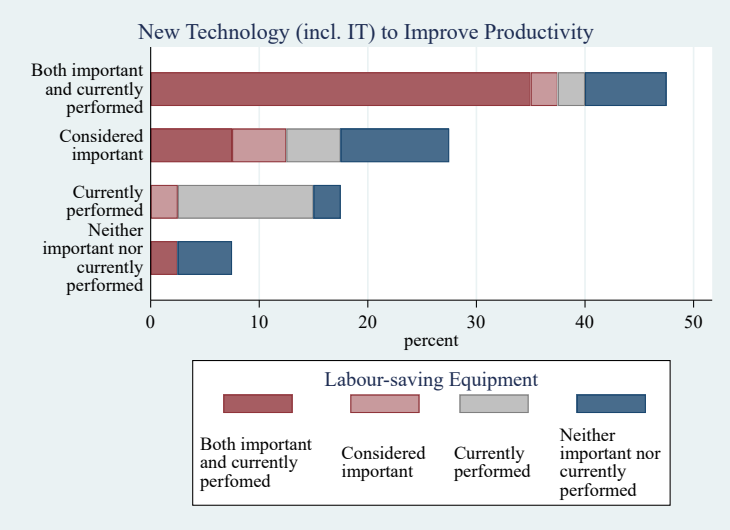



Figure 2 remains focussed on the engagement and perceived value in new technology to improve productivity, but the shading of the bars now represents the extent to which the organisation engages in and values the enhancement of employee education and training. For that engage and value new technology for productivity raising purposes, businesses both value and engage with employee education and training (~90%). This drops dramatically amongst all other categories and for those organisations that neither perform nor consider it important, we see that no enhancement of employee education or training is valued and performed, although approximately one third of these organisations do classify themselves as performing this function.

Figure 2: The use of enhanced employee education or training to improve productivity

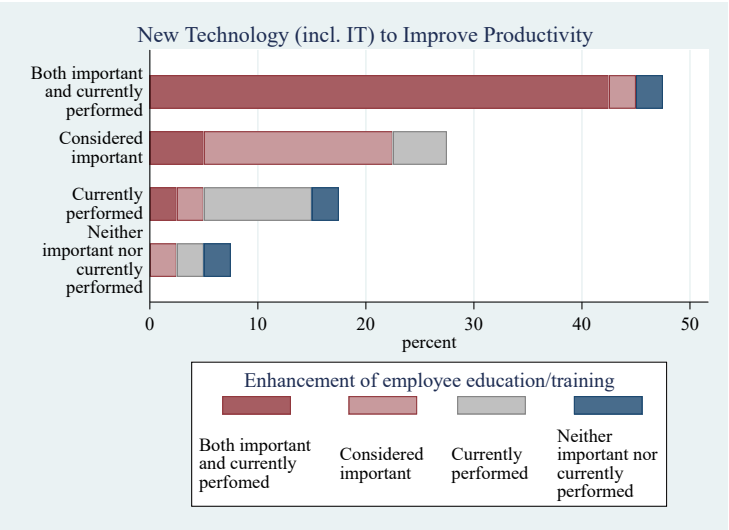



Figure 3 explores the extent to which businesses are engaging with flexible working arrangements, such as working from home (telecommuting). Given the lockdown conditions, this form of working arrangement has been significantly increased before and during the survey period. Again, those that do not consider technology important to improving productivity and not engaged with it, are unlikely to value or engage with working from home within their organisation. Of those that identify technology with productivity improvements, over 50% both engage with and value working from home.

Figure 3: The use of working from home to improve productivity

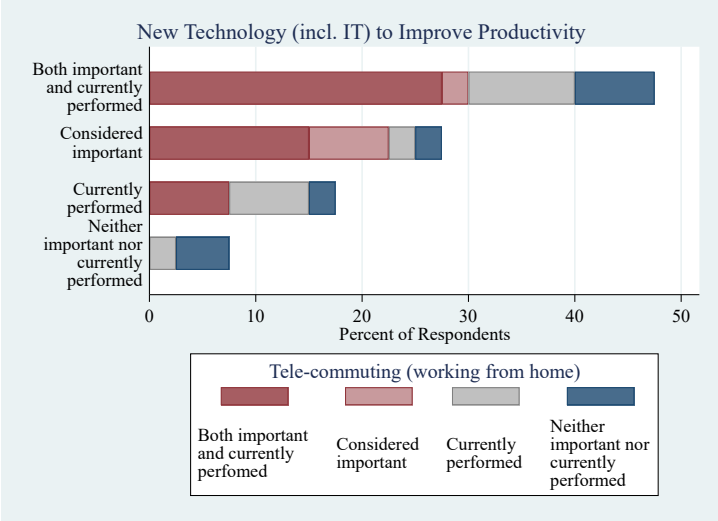
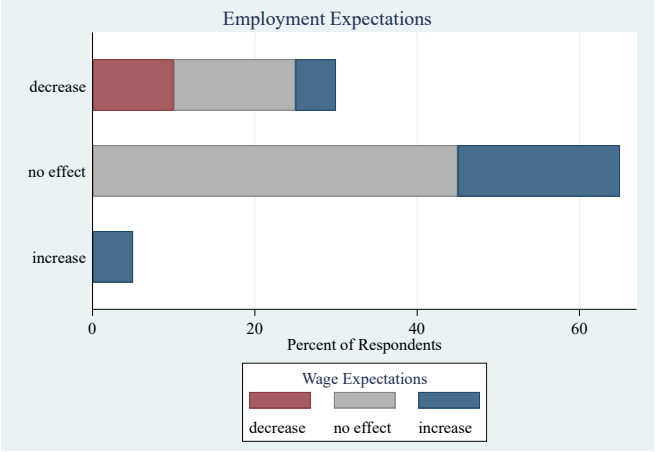



Figure 4 provides an indication of the organisation's view on whether it will be expanding or contracting the number of people it employs. The defining dimension is whether they anticipate employment increasing, remaining the same or falling. Of those anticipating a rise in employment, all respondents felt that wages would rise. However, for those that anticipate a fall in employment, there is a more mixed picture, with a third of organisations feeling that wages would fall. If we consider falling employment opportunities and falling wages, this suggests a decline in labour demand for these organisations, i.e. labour-saving technological change, whereas in instance of increasing employment it might signify technological change complementing workers' skills (and therefore commands a higher wage).

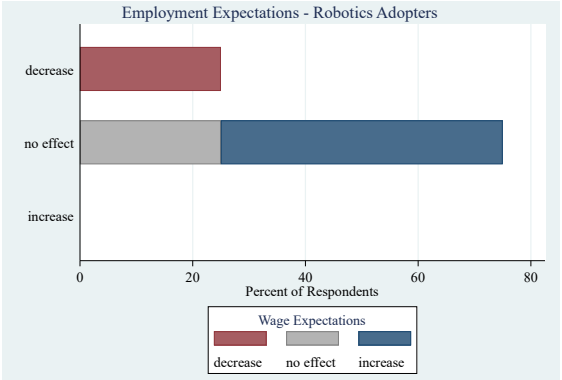
Figure 4: Do you anticipate employment within your organisation to increase, decrease, not change?



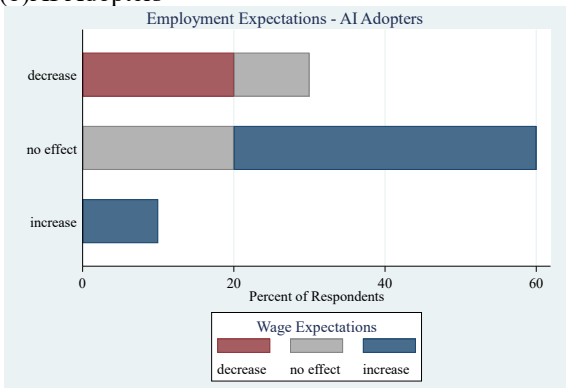

The pilot survey had a smaller number of responses than ideal especially when considering identifying organisations that engaged with the latest technologies (AI, Big Data and Robotics). This has restricted our ability to use statistical methods for analysing associations. However, if we do consider how the data in Figure 4 disaggregates along the lines of technology adoption (Figure 5), we can see that both AI and Robotics adopters by and large, consider these technologies to have limited, possibly decreasing impact on employment in their organisation.

Figure 5: By technology adopting type, do you anticipate wages changing?

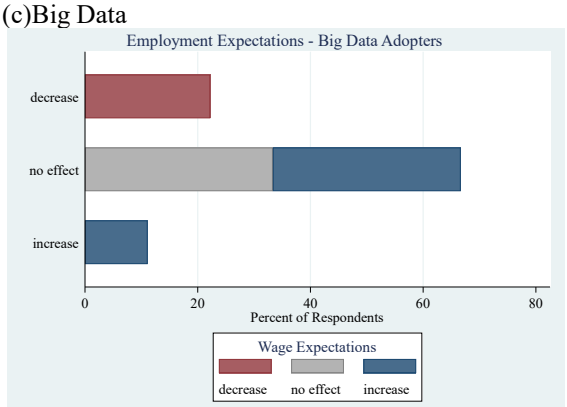
(a)Robotics



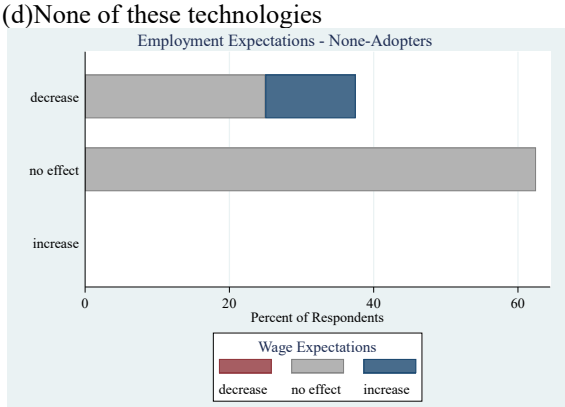

(b)AI Adopters




(c)Big Data




(d)None of these technologies




Also in Figure 5, we see that those engaged with using Big Data overwhelmingly see their workforce remaining the same (+60%) with about half of these respondents expecting there to be a wage increase. Of those respondents expecting to see employment growth, in both AI and Big Data, we see that they also anticipate wages to rise. These findings suggest that there are differences in the way these technologies interact with labour. For technology non-adopters, we see that they anticipate little or no increase in employment for their organisations and some slight recognition that wages will increase going forward.

Figure 6: By your expectations for employment, what do you think will happen to wages?

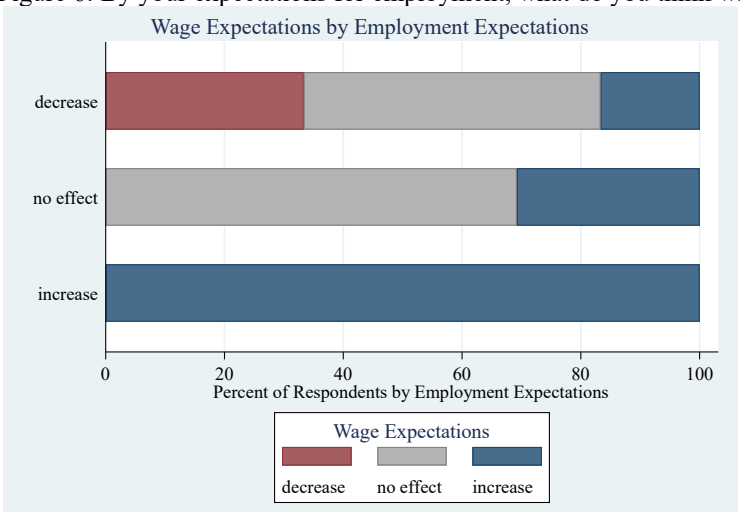



Figure 6 offers a different presentation of the same information in Figure 4, whereby wage expectations are presented as percentages of the overall employment expectations bars. Thus,

we do not see the scale of the differences between employment expectations within the survey but this does give us the clearest indication that those who expect to see employment increase also expect to see wages increase, whereas the possibility of declining wages comes into play only when respondents see employment expectations as declining.

*Skills gaps identified*

Figure 7 presents evidence gathered in relation to skills gaps. We see that 28.6% of respondents often have trouble in attracting the right people, with almost half the respondents also identifying that they sometimes experience difficulties. Thus, we see that three quarters of those surveyed experience some difficulty in finding the right people for the job, indicating that there may be a skills gap (or labour shortage).

Figure 7: "Does your firm experience difficulty in attracting and appointing the right people?" (Q20)

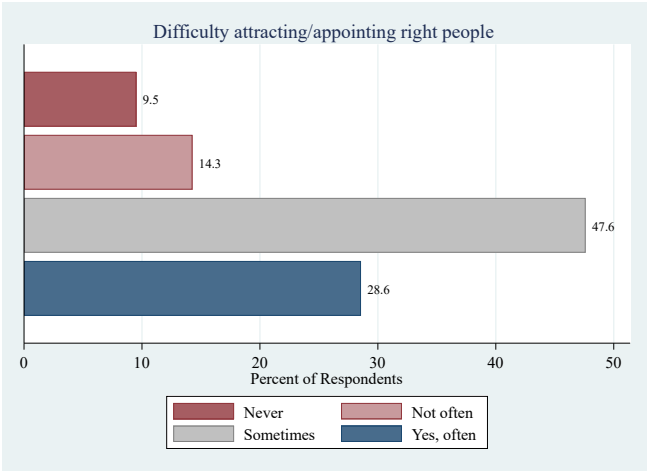
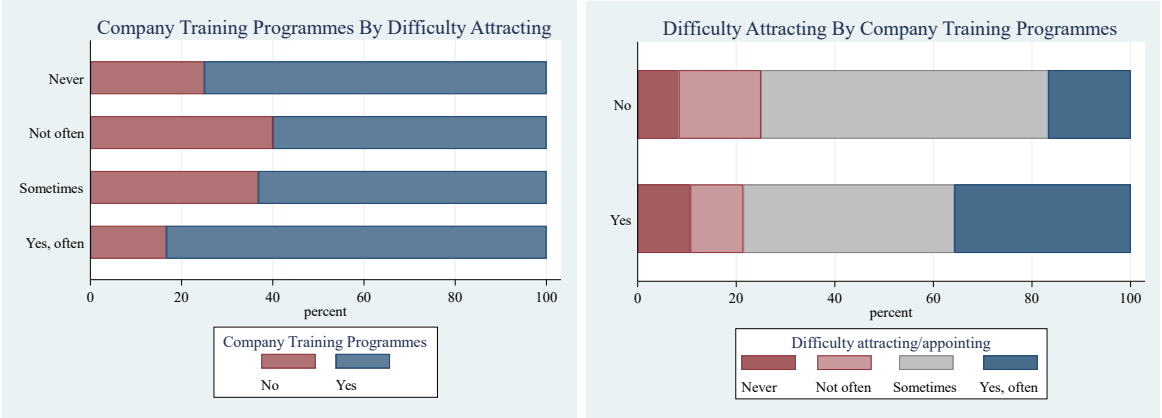



Figure 8 provides a breakdown of the question presented in Figure 7 according to whether they offer in-company training. It is evident that around somewhere between 60% and 80% of organisations offer in-company training, this is highest for those that often have trouble in attracting the right people, and curiously, those that do not experience any difficulty. Those that reported sometimes or rarely struggling to find the right people offered the lowest level of in-company training. This might suggest that those who find it difficult to hire the right workers offer in-house training to compensate for skills gaps. It may also be that those organisations never experiencing challenges in recruiting the right people have recognised the importance of in-house training both in attracting and having the appropriately skilled workforce. Further investigation here would be required.

Figure 8:



To go some way towards understanding the nature of the skills gaps, we again split our data into those technology adopters and compare whether there are any marked differences, either amongst the various technologies or between those that engage with technology compared to those who do not. In the case of those adopting robotics, we see that, adopters seem to experience less difficulty than those who do not – only around 60% experiencing difficulties recruiting the right people sometimes or often, compared with almost 75%. The same is also true on aggregated for those adopting AI technologies, although, compared to those who do not adopt, 25% often experience difficulties in recruiting the right workers, compared with around 20%. For the non-adopters, the 'sometimes' category dominates. Broadly, across all technology categories, the proportion of those never experiencing difficulties recruiting is broadly consistent between those that do and do not engage.

Figure 9: By technology adoption, has your organisation experienced difficulties in attracting the right sort of worker?

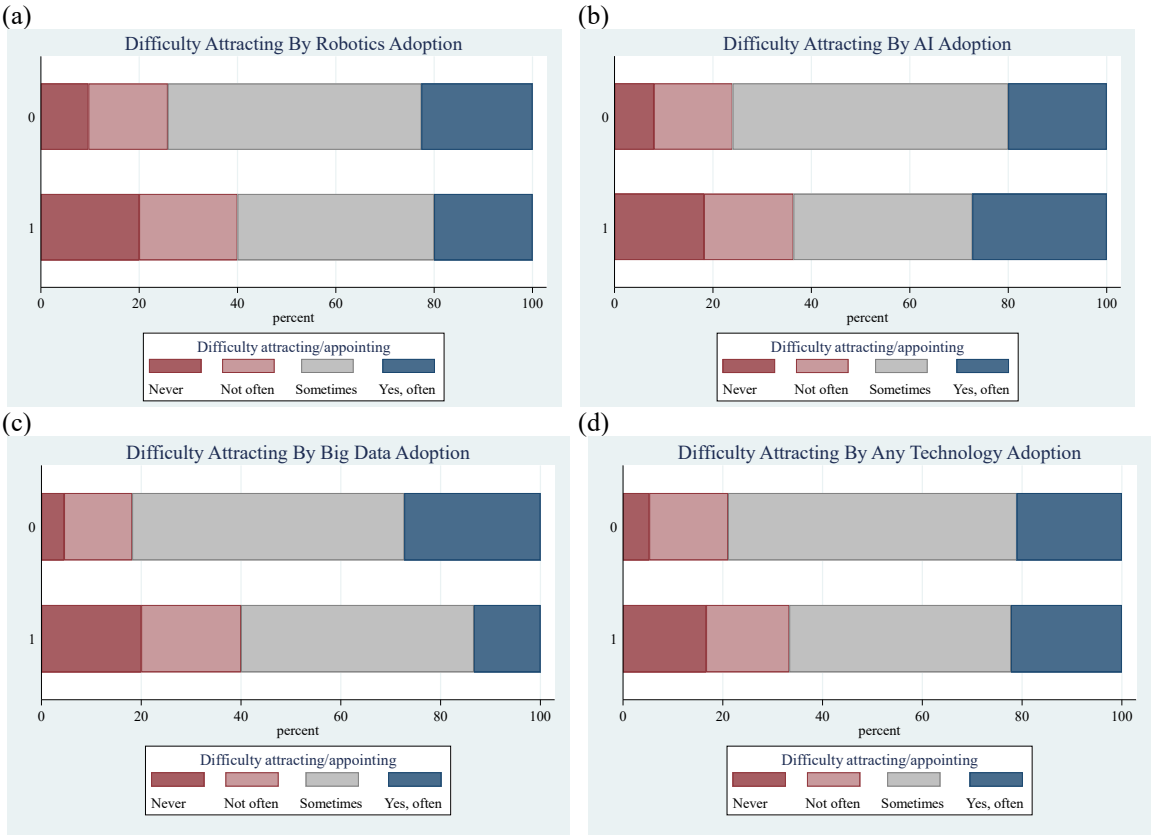



Figure 10 contains further information on the changes that technology adopters have seen in their workforce. Figure 10(a) looks at all firms, while Figure 10(b) focusses on those that are using AI or robotics. We see that in general, organisations have seen little change to their labour force (77%). In the case of adopters, we see that 50% of relevant responses indicate that they engaged in more in-house training and also that they sought to hire workers with appropriate skills in the relevant field of technology.

Figure 10: By use of technologies, has your organisation had to ….

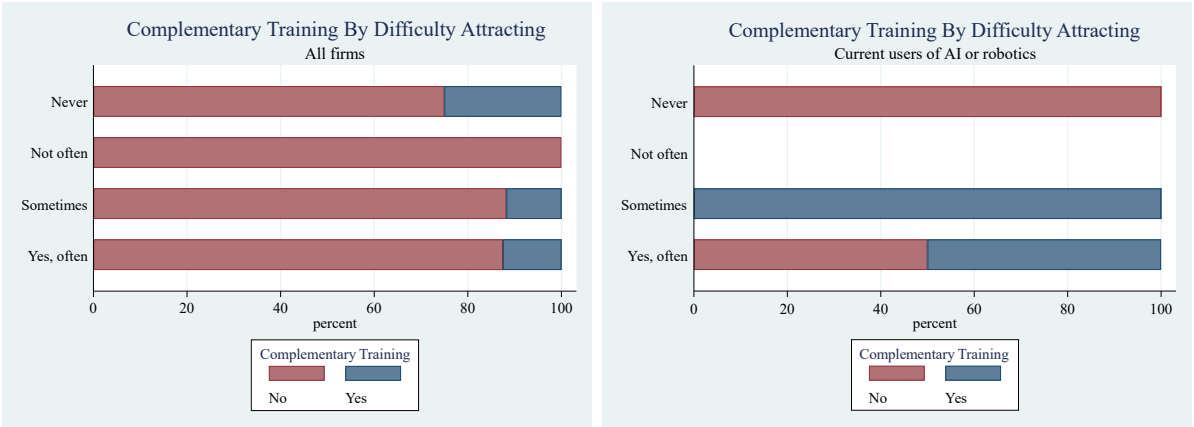
(a) (b)


Note: Respondents could select multiple answers.

Figure 11 provides an overview of whether firms offer training according to their declaration regarding the difficulty of recruiting. We see that except for those respondents that do not often experience recruitment difficulties, some in-house training provision is made. While the difference is not pronounced, we see that those never experiencing shortages offer more in-house training generally, suggesting that in-house training can be regarded as a substitute for a more targeted recruitment strategy. When we focus on those only that engage in technology adoption, we see that the distribution is more marked (in part driven by small sample sizes) and for those experiencing recruitment challenges often do offer training in 50% of the cases. Caution should be placed on the interpretation of Figure 11(b) however, given the small number of responses from technology adopters.

Figure 11: By difficulty in attracting staff, does your organisation offer in-house training?

(a) (b)




## 6. Conclusions & directions for future research

The results of our pilot study provide evidence for the complementarity between skills and the adoption of new technology. While there is already some literature, there is a shortage of quantitative studies that evaluate the interdependencies between this latest wave of technology (AI, Robotics and Big Data) and human capital. Our work goes some way in addressing this gap, albeit with a small sample of SMEs in Kent.

In our novel survey of Kent SMEs, we find evidence that new technologies require complementary skill investments and that firms deem both new technologies and training of their workforce important for productivity. While there is some heterogeneity across the type of technologies introduced, the survey responses suggest that hiring employees with the relevant skills for these technologies or training other employees are strategic substitutes; firms facing difficulties attracting workers with the right skills, are more likely to run own training programmes for employees. This might suggest that there is a skills gap that may be holding back productivity and economic growth.

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