Data foundations and AI adoption in the UK private and third sectors

July 2021

EY
Building a better working world

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1 Executive summary

The Department for Digital, Culture, Media and Sport (DCMS) is a Government department responsible for driving growth, enriching lives and promoting Britain abroad, whilst delivering its policy responsibilities around Digital, Culture, Media and Sport. Part of DCMS's mandate is to support business growth through innovation and the adoption of technology.

DCMS appointed EY to conduct an evidence analysis and primary market research to assess the extent of data foundations and AI adoption. In addition, our research covered the impact of, and barriers to adopting data foundations. To inform DCMS's goals of helping build a world-leading digital economy that works for everyone, this study sets out points of view from organisations across the UK economy – including third sector and small and medium-sized enterprises (SMEs) – on the perceived value of data in decision-making, the adoption and use of data foundations and artificial intelligence (AI), barriers to the adoption of data foundations and the key considerations for Government to address these challenges.

Data foundations is defined in the National Data Strategy as data that is:

- ► Fit for purpose
- ► Recorded in standardised formats on modern, future-proof systems
- ► Findable, accessible, interoperable and reusable (FAIR).[1]

1.1 Methodology

Our approach comprised undertaking a rapid evidence assessment (REA), online surveys and interviews with business leaders across the private and third sector.

REA: The purpose of the REA was to understand the evidence landscape assessing the adoption of data foundations, the barriers and challenges around adopting data foundations, and the Government's role in helping organisations make better use of data. The REA findings were used to help inform the approach to measuring the adoption of data foundations and shape the online survey and interview programme design.

Online surveys: Utilising a third-party survey platform, we surveyed organisations across the UK and received responses from 399 organisations and collected circa 30,000 data points that informed our analysis.

Survey participants were selected to ensure a broad sample size across various parameters, including size, sector, industry and geography (further details are in section 2.2.2). The survey and underlying data were summarised in a dashboard built in Power BI, a business analytics software, to generate deeper insights from the results and inform our findings and analysis.

Interviews: We undertook 26 interviews with business leaders representing organisations from a wide array of industries, locations and organisation sizes. These in-depth interviews offered further insights into the business sentiment and provided qualitative evidence to support our quantitative analysis.

Our research did not attempt to place an economic or monetary value on data. The term 'value of data' as used throughout the report is defined as the importance of data to an organisation's success and the business benefits organisations expect to realise through their data-related initiatives and improvement of data foundations.

As part of our research we have developed four measures to help us analyse the adoption of data foundations (the 'Data Foundations Adoption score'), adoption of AI (the 'AI Adoption Level'), the perceived value of data (the 'Perceived Value of Data score') and the impact of improving data foundations (the 'Improving Data Foundations Impact score').

A comprehensive articulation of our research methodology is set out in section 2 of this report.

1.1.1 Key areas of focus

Our primary research focused on understanding how organisations perceive the value of data in the context of their decision-making, what value can be generated from the adoption and improvement of data foundations and what barriers are deemed most challenging to address. The following sets out the key research questions addressed through the survey and explored further in interviews:

1. Value of data:

To what extent do private and third sector organisations understand the potential value of data? To what extent do they view data as a strategic asset? How do organisational characteristics influence organisations' perceived value of data?

2. Adoption of data foundations and AI:

How can the adoption and improvement of data foundations be measured? What value do the adoption and improvement of data foundations bring to private and third sector organisations? How does improvement in data foundations impact the adoption of AI?

3. Barriers to adoption:

What barriers or challenges prevent organisations in the private and third sectors from adopting or improving data foundations?

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[1] https://www.gov.uk/Government/publications/uk-national-data-strategy/national-data-strategy

1.2 Summary of key findings

The overwhelming response from participants suggests that data is deemed important to the success and growth of organisations across the private and third sector. However, some industries (e.g., Life Sciences, Finance, Industrial Products) expect to derive greater value from improved data foundations than others (e.g., Services and Infrastructure). Government support in helping industries realise greater value from data foundations could positively impact the UK's gross value-add (GVA).

Common challenges around the adoption of data foundations included the availability of staff with relevant data skills, challenges with legacy infrastructure, and lack of funding. These were identified across all sectors and industries of the UK economy. Data-driven interventions could include encouraging organisations to redeploy funds, with a focus on improving data foundations adoption and supporting new job market entrants and experienced professional retraining for more data-enabled, technically focused roles.

Cultural challenges and obtaining buy-in from management are less common issues, which indicates that organisations broadly accept the need to adopt and improve data foundations to operate their businesses in the future successfully. Further details are provided in section 3.3.1.

Our key findings in the three areas of focus are summarised below.

1. Value of data

► 99% of participating organisations agreed that data is important to their success, with 90% of respondents having a data strategy or data-related initiatives in place.

► Organisations expect to realise value from their data strategy and data-related initiatives mainly through increased productivity (60% of respondents), cost reduction (47% of respondents) and improved customer engagement (46% of respondents).

► There were no material differences in the perceived value of data (as measured by the Perceived Value of Data score) between organisations of different sizes, age, AI Adoption Level or geographical location. This varied from the evidence review, in which we identified that larger and younger organisations were more likely to understand the importance of data.[2] This suggests that the understanding of the potential importance of data has become more widespread.

► Although organisations understood the importance of data, we found they have challenges quantifying the value of data, return on investment, and the impact of data improvements. This results in organisations being unable to assess the effectiveness of data initiatives or prepare compelling business cases for investment, which may be constraining organisations' investments in data and data technologies.

► Quality was overwhelmingly identified as the most important data characteristic to an organisation's success, selected by 41% of survey respondents. This was consistent across organisations of different size, age, sector, AI Adoption Level or in different geographical locations.

► There were no material differences in the most important data characteristic between organisations of different sizes, age or sector. However, significant differences were identified between industries. This is explored further in section 3.1.

[2] DataKindUK and Data Orchard (2017) Data Evolution Project Report

2. Adoption of data foundations and AI

► The adoption of data foundations appears to be relatively widespread, with no significant differences in the Data Foundations Adoption score between the size of the organisation, region or industry. However, the level of data foundations adoption in the third sector was found to be relatively low compared with the private sector, consistent with the findings of our evidence assessment. [3]

► Organisations are still at a relatively early stage of their data journey, with many organisations focusing their data strategy on improving data quality and governance (63% of respondents), security (53% of respondents), and data sharing and usability (47% of respondents). However, in our opinion, the greatest value will come from using data to inform responses to genuine organisational challenges and opportunities, and that is still some way off for many organisations.

► Organisations see benefits from improved adoption of data foundations and expect a wide-ranging positive impact, including increased productivity (80% of respondents), revenue generation (75% of respondents), and customer engagement (72% of respondents).

► AI remains an emerging technology with 27% of organisations at Released and Advanced level; 38% of organisations planning and piloting the technology; and 33% of organisations neither having adopted AI nor planning to.

► 56% of respondents are planning to increase investments in AI technologies within the next three years, and only 2 out of 399 survey respondents stated they would decrease investments.

► AI Adoption Level is significantly higher in the private sector, with 70% of private-sector organisations planning or already using AI, which compares with 42% in the third sector.

► Within the UK private sector, 90% of large organisations have planned or already adopted AI, compared with 48% of SMEs.

► From an industry perspective, organisations operating in Finance and Technology, Media and Telecom (TMT) report the highest levels of AI adoption, with 52% of respondents from the Finance industry and 38% from the TMT industry being at the Released level (i.e., AI is put to active use in one or a few processes in the organisation) or Advanced level (i.e., AI is actively contributing to many processes and enabling more advanced tasks).

► There was no linear relationship between adoption of data foundations (as measured by Data Foundations Adoption score) and AI Adoption Level. However, organisations with higher AI Adoption Levels also had a higher Data Foundations Adoption score, indicating that data foundations are a necessary but not sufficient condition for adopting AI.

3. Barriers to adoption

► The key barriers preventing organisations from adopting and improving data foundations are:
  ► Lack of skilled personnel (14% of respondents identified this as the single biggest barrier)
  ► Challenges with existing infrastructure (14% of respondents identified this as the single biggest barrier)
  ► Lack of funding (11% of respondents identified this as the single biggest barrier)

► Cultural challenges and lack of management sponsorship and engagement were the least common challenges (i.e., the most absent of all barriers selected) reported by organisations.

► Frequency of occurrence of barriers, their impact and how they may evolve varies across industries, suggesting barriers to data foundations adoption are industry dependent.

► Barriers also appear to be dependent on the level of data foundations adoption (as measured by the Data Foundations Adoption score). The key challenges (i.e., most frequently selected) for organisations with a relatively low Data Foundations Adoption score include lack of skilled personnel and management buy-in. Conversely, organisations with a relatively high Data Foundations Adoption score reported challenges with existing technology infrastructure, risk of disruption to the organisation, and data-related regulation.

► 68% of respondents agreed that the Government has a role to play in helping organisations use data more effectively. The key data-related Government initiatives respondents would most welcome were:
  ► Investing in providing people with data skills and improving access to workforce with relevant data skills (63% of respondents)
  ► Providing funding to support effective use of data (38% of respondents)
  ► Investment in improving and releasing datasets (37% respondents)

► Based on interviews, there are many instances where public sector data is already available, but it is of varied quality and often not in an easily accessible, usable and consistent format, making it challenging to use by the private and third sectors.

Detailed discussion and analysis of our key findings are set out in section 3 of this report.

[3] Skills Platform, zoe amar digital (2020) Charity Digital Skills report 2020

1.3 Summary of key considerations

The following considerations for Government are based on the findings from our market research and are positioned to tackle the barriers identified by organisations when adopting data foundations and AI.

Data skills

The availability of skilled resources was identified as the most common, and impactful, barrier to the adoption and improvement of data foundations. This was also identified as a key area for Government intervention by survey respondents. The interventions could include policies and actions that will result in an increase in the availability of data analytics, AI and technology skills for young people starting their careers and adults retraining and changing careers.

Data improvement in private and third sectors

Given the significant differences observed in barriers to adopting data foundations and AI across industries, data-related interventions should consider differences between industries.

Data-related policies should consider prioritising:

► **Infrastructure and Services industries**. As these industries are the largest in the UK by GVA, improvement in data foundations that lead to improved insight, decision making and ultimately better commercial and economic outcomes in these industries could have the largest impact on the UK economy.

► **Life Science industry**. Our findings suggest the life science industry may realise the greatest benefits from improved data foundations given the use of emerging technology, data analytics and AI in the sector, together with the move towards personalised medicine.

► **SMEs**. They are lagging in terms of AI adoption, struggle to afford access to data-related technologies and, therefore, may not realise the full potential value of data without some level of intervention. Government data-related policies should consider supporting SMEs to ensure that benefits of improved data and application of data-driven technologies are spread equitably across the UK economy.

► **The third sector**. It is lagging the private sector in data foundations adoption but can generate a significant positive socio-economic impact on society, such as contributing to citizen wellbeing, quality of life, community building or civic engagement.

Data sharing in public and private sectors

Government and the public sector collect, hold and generate huge amounts of data valuable to the private and third sectors. The Government should continue investing in improving the quality, consistency and interoperability of data across the public sector. In many instances, the data is already available, and priority should be given to enhancing these existing datasets rather than releasing new ones.

Government should continue developing initiatives and policies to improve access to and sharing of private sector data, e.g., through exploring data trusts or data cooperatives.

The Government should continue its focus on the communication of data foundations and their importance to supporting the deployment of AI and other emerging technologies that could benefit businesses in the UK.
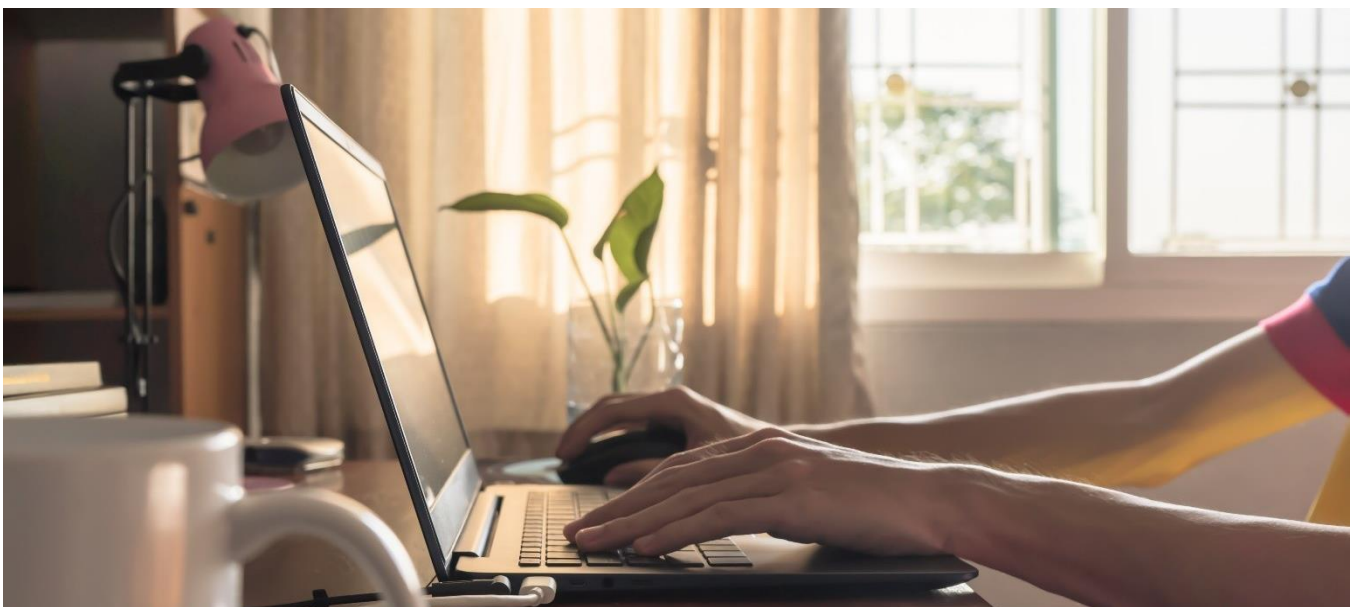
2 Research methodology

Our methodology comprised three distinct but interrelated stages:

1. Rapid evidence assessment
2. Online survey and quantitative analysis
3. Organisation interviews and qualitative analysis

We set out the detailed work we have undertaken in each area below.

2.1 Rapid evidence assessment

The purpose of the REA was to understand the evidence landscape for:

► Data foundations adoption

► Barriers and challenges to adopting data foundations

► Government's role in helping organisations make better use of data

The findings from the REA were then used to define the approach to measuring the adoption of data foundations and the impact on organisations of improving data foundations. The REA also helped to inform the design of the online survey and interview programme.

The following criteria were used to select appropriate documents for review in the REA:

► **Quality assessment:** Only authenticated and reputable sources were included

► **Inclusion and exclusion criteria:** Searches were conducted using the following seven criteria:

1. **Geographic focus:** Europe and UK focused.
2. **Language:** Only studies available in English were included.
3. **Research design:** Primary, empirical research or evaluation (quantitative or qualitative) or secondary reviews.
4. **Date of publication:** Materials published from 2015 onwards were included.
5. **Relevance:** Studies must explore the relationship between data foundations and the private/third sector in the UK.
6. **Types of publication:** Academic journals, peer-reviewed materials, working papers, grey literature, books, policy papers and book chapters available online at no cost to the reader. This excluded scanned copies and Google Book previews.
7. **Cost of access:** Materials were included only if free to access. Those requiring payment were excluded.

► **Data sources looked at:** Key databases such as EMIS, Thomson One and IDC and Google Scholar.

Having applied these criteria, we identified 24 documents (listed in Appendix C) that were selected for further review. The key themes identified from the REA that informed the survey design and interview questionnaires are set out in Figure 1 below.

Figure 1 Key themes from the REA

No.	Research areas covered	Key themes identified
1.	Data foundations understanding and adoption across organisation characteristics	1. **Definition**: Data foundations as a definition was used to a limited extent, and various terms were used to define similar concepts, such as big data, data science, data analytics or data maturity. 2. **Measurement**: There is no commonly agreed, structured methodology to measure adoption and improvement of data foundations and the impact of adopting and improving data foundations. 3. **Size and age of organisation**: Larger organisations, companies with higher revenue (defined as an annual turnover of more than €1 million) and those which are young (less than 11 years old) were reported to have a greater understanding of the importance of data.[4] 4. **Industry trends**: TMT and Finance industries were found to be more mature in terms of using data. Life Sciences appeared to be less mature.[5] 5. **Third sector**: Found to be less mature in terms of using data, e.g., 88% of charity professionals found to be fair to poor at using, managing and analysing data. However, using data effectively is one of the key priorities post COVID-19 pandemic.[6]
2.	Barriers to adopting and improving data foundations	Five key barriers to adopting and improving data foundations were reported in the documents reviewed during the REA. These are set out below: 1. **Changing technology landscape**: The speed at which data and AI technology is advancing makes it challenging for organisations to decide when and where to invest. This uncertainty is contributing to delays in investment in data and AI technologies. 2. **Lack of skills**: Organisations struggle with a lack of skills to implement, maintain and improve their data capabilities. Skills may be lacking across a range of data areas such as governance, architecture, analytics or cybersecurity. 3. **Cost**: Adopting and improving data can require significant investments in IT infrastructure, talent and developing data policies, frameworks and processes. These significant upfront and ongoing costs, combined with challenges to reliably determine the return on investment, lead to some organisations being nervous about allocating scarce capital and resources to this area. 4. **Data sharing issues**: Technical, regulatory and other challenges with sharing data across organisations and geographies, particularly on a timely basis, limits the potential value that could be realised from data. 5. **Integration**: Data is typically obtained from multiple sources and channels (e.g., social media, surveys, market reports, admin systems). It often needs to be curated and integrated across these channels to drive actionable insights. This can be expensive, and challenges with data integration also limit the value that can be derived from data.
3.	Government role	1. **Setting the market framework**: Government has a role in setting the conditions under which the use and sharing of data takes place, e.g., with regards to intellectual property rights, legal and regulatory frameworks around the use of data and digital technology, industry-specific regulations. 2. **Addressing market failures and adjusting market outcomes**: Government can address market failures, e.g., incentivising organisations to share data where there is a social benefit or improve market outcomes for specific segments of the economy and population (e.g., vulnerable consumers). 3. **Support research**: Government can support further research around data, e.g., explore institutional models that can support trustworthy access to data, such as data trusts, pools, cooperatives and clubs.

This output from the REA was then used to inform the structure and content of the online survey and interview programme.

[4] DataKindUK and Data Orchard (2017) Data Evolution Project Report
[5] Whishworks (2019) The State of Big Data in the UK 2019
[6] Skills Platform, zoe amar digital (2020) Charity Digital Skills report 2020

2.2 Online survey and quantitative analysis

2.2.1 Approach to the survey design and launch

We focused the online survey on data foundations, as specifically defined by the National Data Strategy. The data foundations definition was explained and used throughout the survey and interviews to ensure i) it was a term that was fully understood by respondents and ii) a level of consistency in responses that could be analysed robustly.

We linked the survey questions asked of respondents directly to the specific research questions for this study. Full details of the online survey questions are included in Appendix A.

The survey questionnaire and microsite were designed by EY with input from DCMS between mid-January through mid-February 2021. The survey was first piloted with 40 randomly selected organisations, applying quotas to ensure the pilot survey covered a range of industries, locations and different-sized businesses. The pilot survey was used to test the time to complete the questionnaire and analyse the quality of responses in supporting our research questions. Based on the pilot findings, minor changes were made to the questionnaire. As the changes were not material, these pilot responses were included in the findings.

The survey questionnaire was formally launched in February 2021 via a leading third-party survey platform and was shared by the third party with their wide survey community, targeting relevant personnel within organisations who influence, decide or are actively involved in key data-related activities in their organisation. The survey responses were gathered over 15 days.

To enhance the reliability of the survey results, robust quality assurance procedures were applied to minimise data collection errors and ensure that only full and properly considered responses were included in the subsequent analysis. These included:

► Implementing proven data screening methods such as screening questions, response times and invariant responding (i.e., the same option selected repeatedly)

► Daily monitoring, including progress against sample targets and analysis of total responses and complete responses

► Regularly visualising and analysing responses to identify and explore any responses that appeared unusual

Based on the quality procedures applied, this report is based on a cross-sector, cross-industry and cross-region survey of UK organisations, which provided 399 quality respondents (out of 1,139 total responses received) and a rich dataset of circa 30,000 data points. This enabled a robust comparative analysis of results across industries, sectors and organisation size.

2.2.2 Sector and geographic sampling

Segmenting the organisations in the UK to determine what would be a representative sample of the UK economy for this study could legitimately be done in a number of ways, such as: by contribution to GVA, turnover or number of employees. However, for the purpose of this study we agreed with DCMS to stratify the targeted sample of respondents using an average of GVA contribution, turnover, and number of employees.

We then adjusted the sample from SMEs (as the REA findings suggested they are likely to have a lower adoption of data foundations) and Scotland, Wales and Northern Ireland (as the regions may have been underrepresented in other studies). This segmentation and sample design ensured broad coverage of:

► **Organisation sizes:** SMEs: <250 employees and Large: >250 employees). Sole traders were excluded from our study.

► **Sectors:** Private and third sector

► **Industries:** Consumer Products & Retail (CPR), Infrastructure, Industrial Products, Services, Technology, Media & Telecom (TMT), Finance and Life Science

► **Geography** (based on primary activity of the organisation)**:** London, North of England, South of England (excluding London), Midlands, East of England, Scotland, Wales, Northern Ireland

2.2.3 Survey data sample

The survey fieldwork yielded 399 completed responses of an appropriate quality, which gives a +/- 5% margin of error at 95% confidence level. Private sector respondents accounted for some 359 of the completed responses (SMEs: 57%; Large: 43%) and there were 40 respondents from third sector organisations.

Respondents from the private sector were asked about the primary activity of their business based on UK Standard Industry Classification (SIC) and then categorised into seven industries for reporting purposes (Mapping of industry sectors can be found in Appendix B).

Figure 2   Primary activity of the organisations in the survey sample
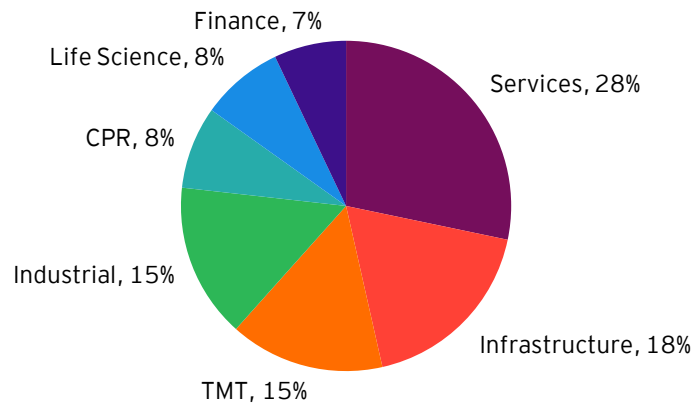
Geographic data was collected at the Nomenclature of Territorial Units for Statistics (NUTS) level 1 and then summarised for reporting purposes into eight regions, presented in Figure 3 below. London, South of England and North of England are the top three regions of primary activity of businesses, representing more than 50% in the survey sample, with 20%, 18% and 15% of respondents, respectively.

Figure 3   Primary region of business activity of the organisations in the survey sample
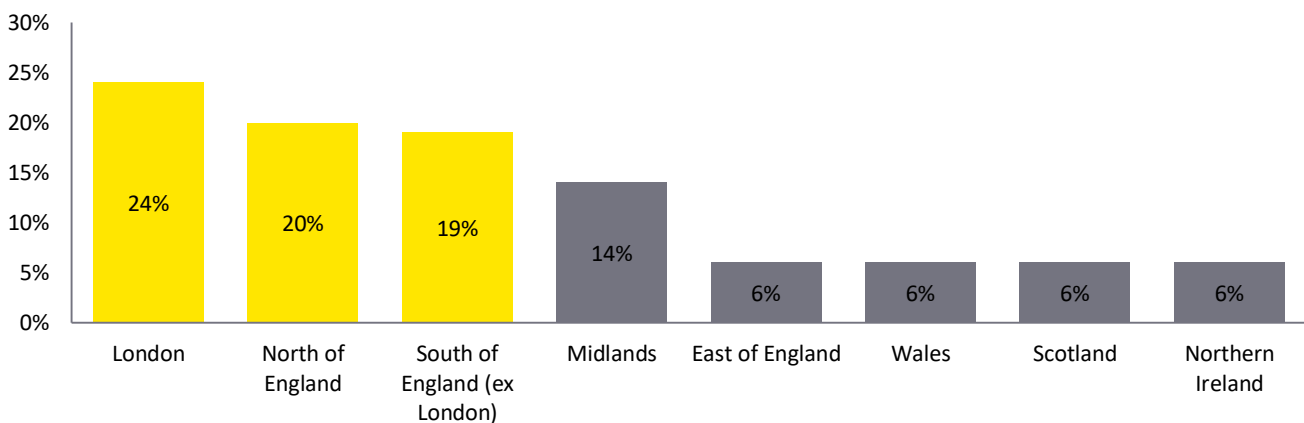
Of those organisations that responded to the survey, 44% of survey participants were senior managers, owners and partners, and 34% were middle management (e.g., Department Head) with responsibility for driving the data agenda in their organisations. Their input is likely to reflect the general perspective and strategic direction of the organisations they represent.

Figure 4 Job role of respondents in the survey sample

Responses by current job role

Job role	%
Middle Management (Director/Divisional/Department Head)	34%
Owner/Partner	22%
Senior Management (CEO/VP/Managing Director)	22%
Experienced Professional or Non-Management	11%
Front Line Management	10%
Home Based Business Owner	1%
Other (please specify)	0%
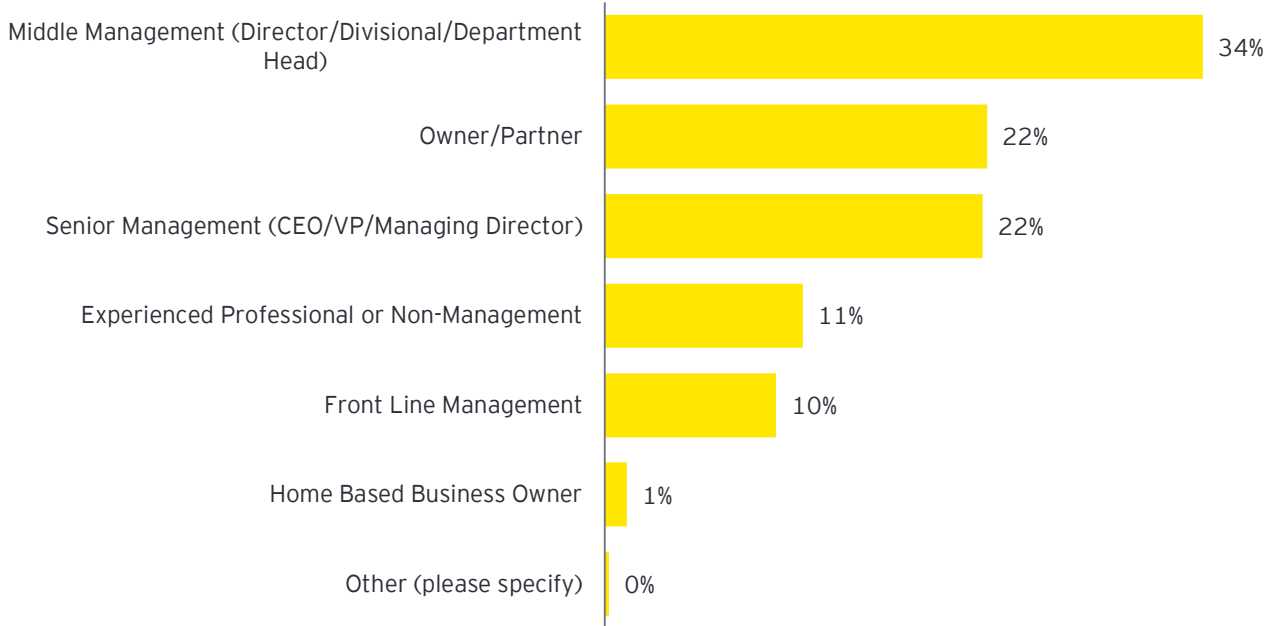
The survey captures responses from organisations with total estimated annual revenue brackets from £0k–£50k to £500m+ and with number of employees brackets from 1-9 to 10k+. This is presented in Figure 5 below. 71% of organisations in the sample have revenue below £50m and 60% have between 1 to 249 employees.

Figure 5 Annual revenue and number of employees for organisations in the survey sample

Responses by annual revenue of organisation

Revenue	%
£0-£50k	5%
£50k-£100k	8%
£100k-£250k	6%
£250k-£500k	6%
£500k-£1m	9%
£1m-£10m	22%
£10m-£50m	15%
£50m-£100m	7%
£100m-£500m	9%
£500m+	9%
Don't know	5%
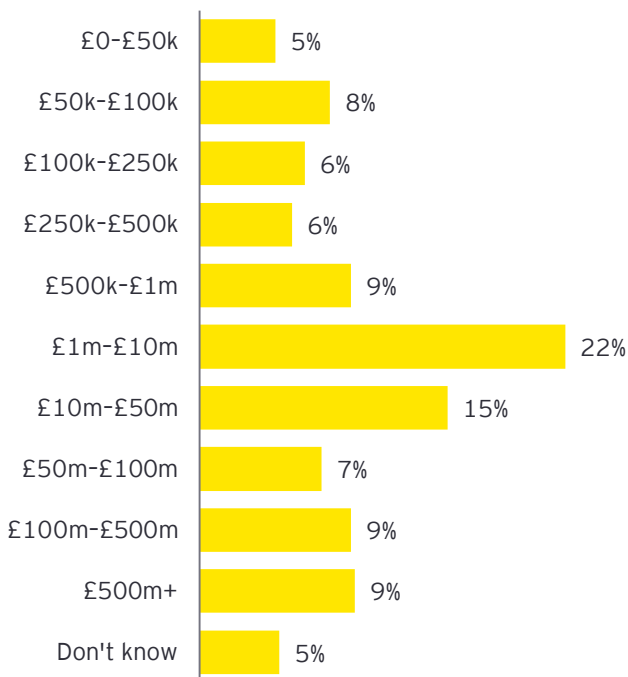
Responses by number of employees within the organisation

Employees	%
1-9	20%
10-49	16%
50-249	24%
250-500	13%
500-1k	9%
1k-10k	14%
10k+	4%
Don't know	0%
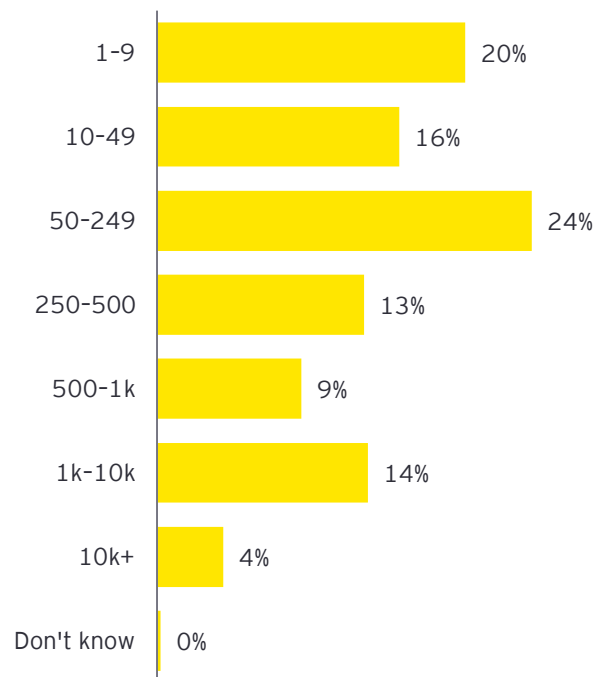
2.2.4 Approach to measuring adoption of data foundations and AI, the perceived value of data and the impact of improving data foundations

As part of the project we developed a number of measures to help us assess the adoption of data foundations and AI, the perceived value of data and the impact of adopting and improving data foundations. These measures are summarised below.

2.2.4.1 Approach to measuring adoption of data foundations

There is no agreed methodology or quantitative approach for measuring the adoption of data foundations. Therefore, we assessed data foundations adoption by asking organisations to self-report on a scale of 1 to 5 (with 1 being 'Strongly disagree' and 5 being 'Strongly agree') as to whether their data is typically of required quality, consistent, accessible, properly documented, easily usable, interoperable, secure and timely (as defined in Figure 6 below).

The indicative level of an organisation's data foundations adoption was then based on a single score (the **'Data Foundations Adoption score'**) calculated as the average (mean) of the scores from responses to these specific questions about data characteristics. We believe this approach is more reliable than asking organisations to self-report their level of data foundations adoption and gives insight to the relative adoption of the constituent parts as set out below:

Figure 6 Data characteristics applied to determine indicative level of data foundations adoption	
Quality	Accurate, free from error and missing values
Consistent	Recorded in standardised formats
Accessible	Easily retrievable when needed
Properly documented	Appropriately catalogued, allowing data to be easily found
Easily usable	Easy to understand and manipulate for organisation's need
Interoperable	Can be easily combined with other datasets and used across different systems
Secure	Appropriately protected against unauthorised access and usage
Timely	Sufficiently up to date for organisation's needs

These data characteristics are based on the data foundations as defined in the National Data Strategy and have been expanded to include two additional characteristics for security and timeliness. The data characteristics were also used to analyse how organisations perceive value of data.

For the purposes of the analysis, we have used the following definitions:

► Low data foundations adoption - Data Foundations Adoption score below 3
► High data foundations adoption - Data Foundations Adoption score greater than 4.5

2.2.4.2 Approach to measuring adoption of AI

For the purpose of this research, AI was distinguished from other data-driven technologies and included a broad range of technologies such as natural language processing (NLP), machine learning, speech recognition, neural networks and deep learning, text analysis, smart robotics, biometrics, virtual agents and computer vision.

To determine the organisation's level of adoption of AI, we asked respondents to self-report their current AI adoption level (the **'AI Adoption Level'**), grading themselves against the following scale:

► None (not yet thinking about AI)
► Planned (AI is being planned, but not yet put to active use, not even in early-stage pilots)
► Piloting (AI is put to active use, but still only in early-stage pilots)
► Released (AI is put to active use in one or a few processes in the company, but still quite selectively, and/or not enabling very advanced tasks)
► Advanced (AI is actively contributing to many processes in the company and is enabling quite advanced tasks)

For the purposes of the analysis, we have defined AI laggards and leaders as follows:

► AI laggards – organisations that graded themselves as None on the AI adoption scale above (33% of respondents)
► AI leaders – organisations that graded themselves as Released and Advanced on the AI adoption scale above (27% of respondents)

2.2.4.3 Approach to measuring the perceived value of data

In this report value of data is defined as the importance of data to an organisation's success and the business benefits organisations expect to realise through their data-related initiatives and improvement of data foundations.

Survey participants were required to rate on a scale of 1 to 5, (with 1 being 'Not important' and 5 being 'Critically important') how important data characteristics (specified in Figure 6) were to the success of their organisation. The indicative level of an organisation's perceived value of data (i.e., importance to the organisation's success) was then based on a single score (the **'Perceived Value of Data score'**) calculated as the average (mean) of the scores from responses to these specific questions about the data characteristics.

2.2.4.4 Approach to measuring the indicative impact of improving data foundations

To analyse the indicative impact of improving data foundations, we asked respondents to self-report the impact of improved data foundations on various aspects of their organisation, including revenue generation, employment generation, productivity or costs (further details are provided in Appendix A, question 6).

Positive impacts were assigned a score from 1 (minor positive impact) to 5 (positive transformational impact). Negative impacts a score from -1 (minor negative impact) to -5 (negative transformational impact). No impact was assigned a 0.

The indicative impact to an organisation of improving data foundations was then based on a single score (the **'Improving Data Foundations Impact score'**) calculated as the average (mean) of the scores from response to these specific questions about the areas impacted by improved data foundations.

## 2.3 Organisation interviews and qualitative analysis

To further supplement the findings from the survey, we conducted 26 deep-dive interviews with senior personnel responsible for influencing or making decisions regarding data strategy and data-driven activities within their organisation. The interviews were carried out in February and March 2021 through video and audio conferencing and followed a structured interview guide agreed with DCMS. Among the interviewees, 55% of respondents were senior managers, owners or partners in the organisations they represented.

The interviewees were asked to complete the online survey before the interview. Their responses were used to focus the discussion on specific areas of interest we had identified for them as organisations, but also more broadly for the study from the preliminary analysis of survey responses. The interviews focused on the key questions for the overall study and typically covered perspectives on the:

► Importance of data to their organisation's success

► Current level of data foundations and AI adoption

► Objectives of the organisation's data strategy and data-related initiatives

► Expected impact of adopting and improving data foundations

► Current and future barriers and challenges to adoption and improvement of data foundations

► Role of Government in supporting organisations within their industry to make better use of data

The interviews were used to further validate and augment the survey findings. Figure 7 below shows the split of interviewees by sector, industry and region.

Figure 7   Split of interviews by sector, industry and region
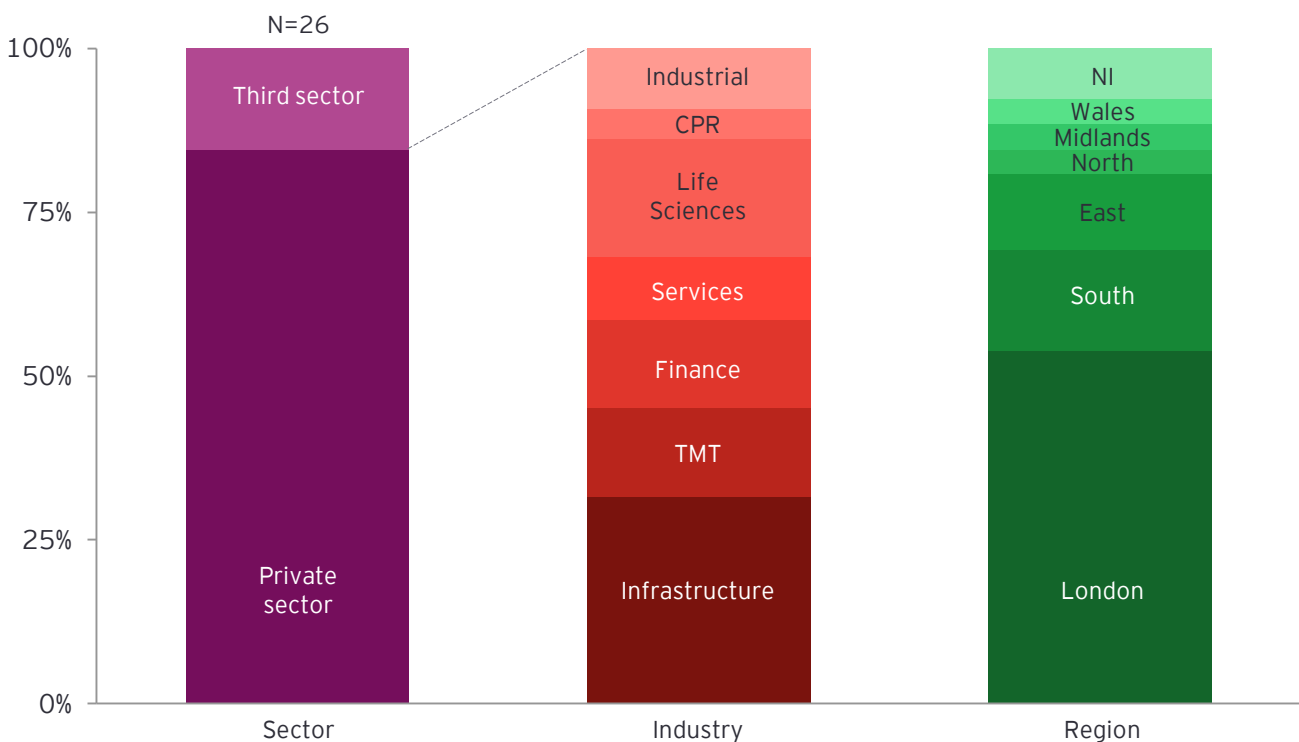
2.4 Methodology limitations

This report follows a robust research design and protocol to minimise potential bias, e.g., self-selection bias, but does not eliminate it, as it is inevitable in market research. However, the combination of interview data, survey data and evidence review gives a solid basis to provide a view on data foundations and AI adoption.

The survey focused on a subjective view of data foundations. This methodology was chosen based on the definition of data foundations in the National Data Strategy and due to our findings from the REA that 'there is no commonly agreed, structured methodology to measure adoption and improvement of data foundations'. Although this approach offers insight into the relative maturity of organisations, the methodology could be improved upon by using a standardised, absolute measure of data foundations adoption. This would remove an element of subjectivity from the survey respondents and would provide more clarity on absolute maturity levels.

Given the sample size, we are unable to analyse responses based on multiple criteria e.g., organisation size and industries. Increasing the sample size of the survey to enable comparisons within industry sectors across different regions would provide further detail on the UK's adoption of data foundations and AI.

2.5 Interpretation of results

All survey responses were visualised in Power BI, a Microsoft analytics and visualisation application. The detailed responses to each survey question could then be analysed in many different and insightful ways, including by size, sector and industry to identify patterns and trends and highlight key findings.

The initial findings were further tested and refined through the interview programme, against the REA findings and through our extensive experience of providing data-related professional services to multiple client organisations.

The survey data is not fully representative of the entire UK business population due to the increased focus on devolved nations and SMEs within the survey respondents. However, in our view, the responses do provide a reasonable estimate of UK businesses adoption of data foundations and AI.

The qualitative insights gathered from the interviews illustrate case studies of real UK businesses adoption and challenges with adopting data foundations. These provide further details and context for the findings that emerged from the survey. As with all qualitative analysis, these insights are not meant to be statistically representative.

In conclusion, we believe that the combination of the evidence review, extensive online survey data, interview data, and our wider market experience gives a solid foundation to provide insightful responses to the specific research questions of this study.

3 Findings from the primary research

This section of the report sets out our findings from the primary research, grouped under the following sub-headings:

▶ **Value of data: the extent to which organisations see value in data (i.e., importance of data to the organisation's success)**

▶ **Adoption of data foundations and AI: the extent to which organisations have adopted data foundations and AI**

▶ **Barriers to the adoption of data foundations: The perceived barriers to adoption of data foundations and the insight this could give to the UK Government.**

We address each in turn below.

3.1 Value of data

> **"**
>
> Data certainly has a large value and even more so through the combination of data assets
>
> Financial Services organisation

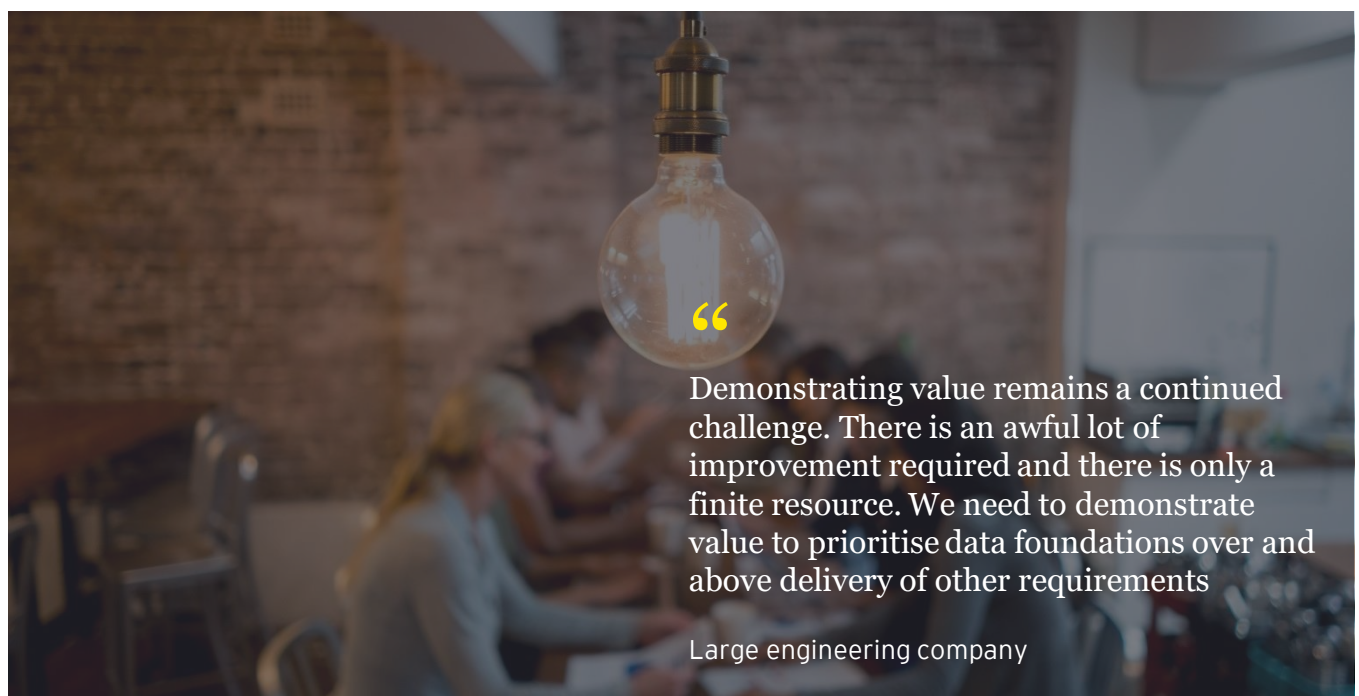These findings relate to the following specific research questions:

▶ To what extent do private and third sector organisations understand the potential value of data?

▶ To what extent do they view data as a strategic asset?

▶ How do organisational characteristics influence organisations' perceived value of data?

To address these research questions, we asked survey participants to rate the importance of various data characteristics to the success of their organisation, whether they have a data strategy or data initiatives and what are the expected benefits and impact of improving data foundations. Our qualitative analysis also explored when and why data became a priority for the organisation, whether recent events, such as the COVID-19 pandemic or EU exit, impacted the perceived value of data (i.e., the importance to the organisation's success and the business benefits organisations expect to realise through their data-related initiatives and improvement of data foundations) and whether organisations can quantify the monetary value of their data and impact of adopting and improving data foundations. To help us measure and analyse the perceived value of data we have developed the '**Perceived Value of Data score**'. Further details are in the Research Methodology section 2.2.4.
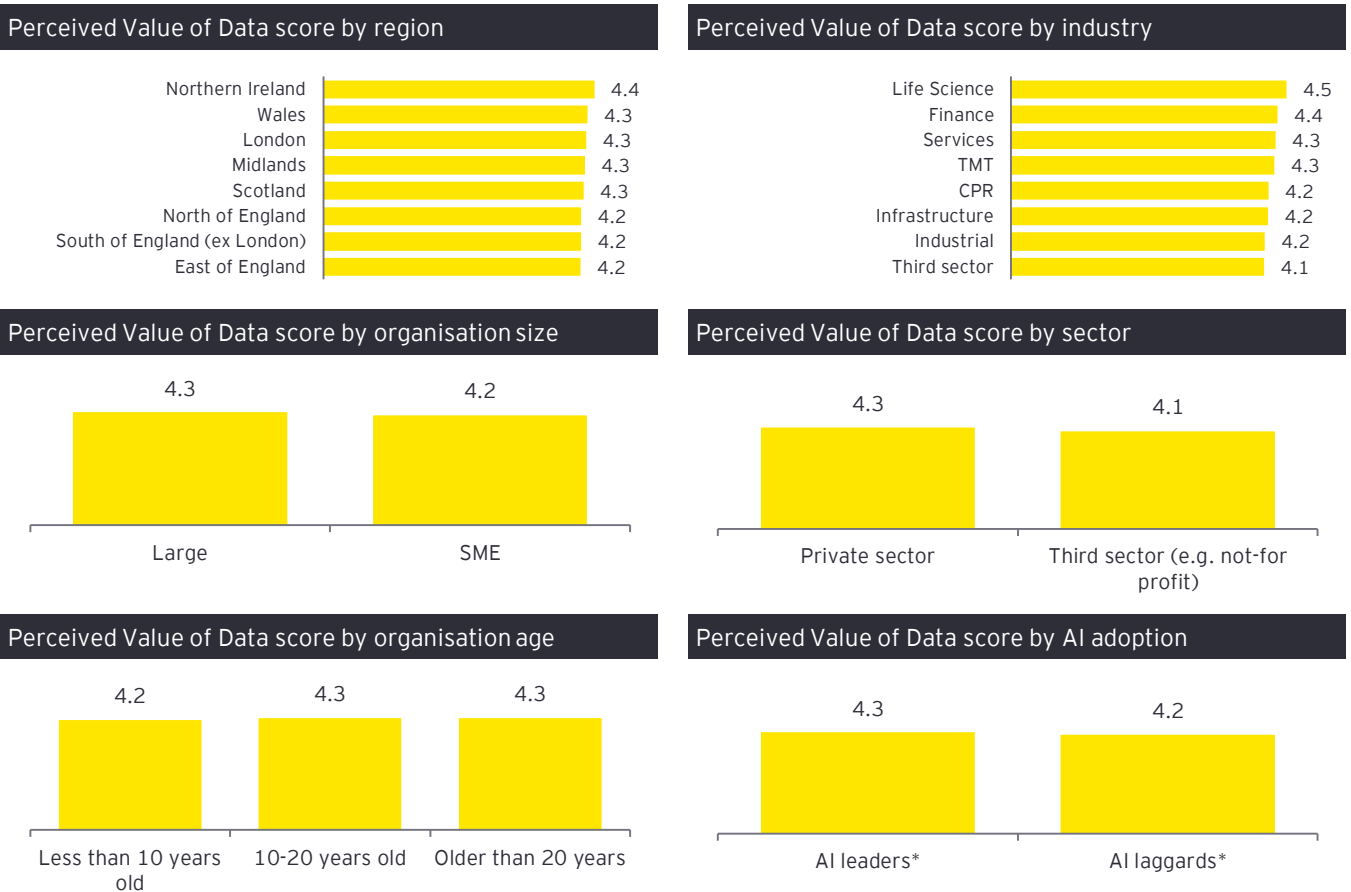
Our key findings in this area are summarised below:

▶ 99% of survey participants noted that data is at least moderately important to the success of their organisation and our interviews also confirmed that data is an organisational priority.

▶ 90% of respondents indicated they have a data strategy or data-improvement initiatives in place. This suggests organisations are maturing in their approach to using data and understand strategic decisions are required to unlock the value of their data.

▶ Organisations expect to realise a wide range of benefits from their data strategy and data-related initiatives, including increased productivity (60% of respondents), cost reduction (47% of respondents) and improved customer engagement (46% of respondents).

▶ Increased productivity was the leading benefit across all organisation characteristics. Cost reduction was identified as the second largest benefit for AI leaders, large, young and private sector organisations, whereas it is improved customer engagement for SMEs, third sector, older organisations and AI laggards.

▶ Interviewees indicated that their data strategy and data-related initiatives could increase productivity and reduce costs through decreasing number of errors in data, supporting process automation (particularly in back office, admin and finance functions), reducing time to find data and perform analysis and providing management with greater insights and visibility to manage performance. This suggests organisations are aware how data can be used to realise benefits.

- The least common benefit expected from data strategies and initiatives is improved environmental sustainability (18%). This may suggest organisations do not see sustainability as important relative to other business areas or they may not be fully aware how better data can support sustainability efforts.
- AI leaders (i.e., organisations that graded themselves as Released and Advanced on the AI adoption scale) expect their data strategy and initiatives to support further deployment of AI (41%) and other data-driven technologies (30%). 0% of AI laggards are expecting their data strategies and initiatives to support AI deployment and only 6% are expecting their data strategies and initiatives to support deployment of other data-driven technologies. This could lead to widening the gap between AI leaders and laggards in adoption of AI and other data-driven technologies. Further analysis of expected benefits of data strategies and initiatives is provided in Appendix D, Supplemental Analysis.
- 94% of organisations that have a relatively high Perceived Value of Data score (i.e, greater or equal to 4.75) have a data strategy or data-related initiatives (in comparison to 73% of organisations with a relatively low score, i.e., below 4.0). The data strategies and data initiatives of organisations that have a high Perceived Value of Data score focus more on improvement in data sharing and usage (62% vs 29%), improvement in data protection (65% vs 34%) and improvement in data quality, integrity and governance (78% vs 49%).
- In comparison to organisations with low Perceived Value of Data score, organisations with a high score expect to realise value from their data strategy more often through increased customer engagement (61% vs, 29%), better risk management and compliance (61% vs 29%), supporting deployment of AI (37% vs 8%) and cost reduction (59% vs 26%). Further information on expected benefits from data strategy and/or data-related initiatives is provided in Appendix D, Supplemental Analysis.
- Our qualitative analysis found organisations usually struggle to quantify the value of data, return on investment and the impact of data-related initiatives.
- As per Figure 8 below there were no material differences in the Perceived Value of Data score between organisations of different sizes, age, sector, AI Adoption Level or in different geographical locations. However, minor differences were identified between industries with respondents from Life Sciences and Finance industries identifying data as more important than respondents from other industries.

> Demonstrating value remains a continued challenge. There is an awful lot of improvement required and there is only a finite resource. We need to demonstrate value to prioritise data foundations over and above delivery of other requirements

Large engineering company

Figure 8 Perceived Value of Data score by key organisational characteristics

Perceived Value of Data score by region

Region	Score
Northern Ireland	4.4
Wales	4.3
London	4.3
Midlands	4.3
Scotland	4.3
North of England	4.2
South of England (ex London)	4.2
East of England	4.2

Perceived Value of Data score by industry

Industry	Score
Life Science	4.5
Finance	4.4
Services	4.3
TMT	4.3
CPR	4.2
Infrastructure	4.2
Industrial	4.2
Third sector	4.1

Perceived Value of Data score by organisation size

Large	SME
4.3	4.2

Perceived Value of Data score by sector

Private sector	Third sector (e.g. not-for profit)
4.3	4.1

Perceived Value of Data score by organisation age

Less than 10 years old	10-20 years old	Older than 20 years
4.2	4.3	4.3

Perceived Value of Data score by AI adoption

AI leaders*	AI laggards*
4.3	4.2

* Definition of AI leaders and laggards is provided in the Research Methodology section 2.2.4.2

We asked survey respondents to select the data characteristic that was most important to their success. This was to help identify those data characteristics that could be prioritised from a policy perspective.

We found that Quality (i.e., data that is fit for purpose in terms of an organisation's decision making) was overwhelmingly identified as the most important data characteristic to an organisation's success, selected by 41% of survey respondents. This was consistent across organisations of different sizes, age, sector, AI adoption, or in different geographical locations.
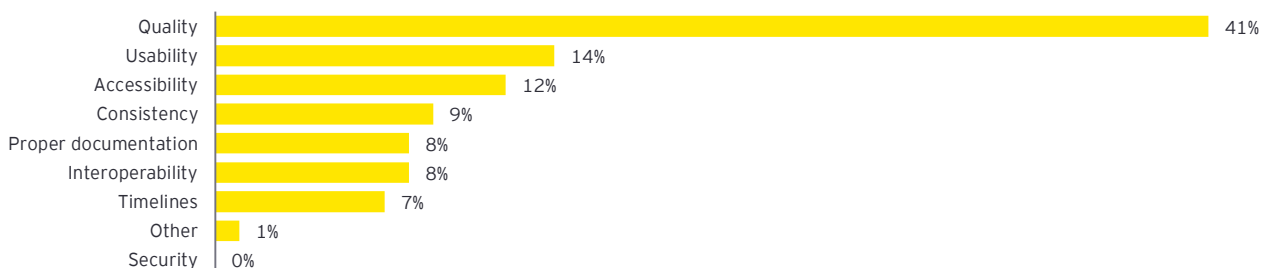
There were no material differences in the most important data characteristic between organisations of different sizes, age or sector. However, significant differences were identified between industries, e.g., 3% of Life Science organisations identified Accessibility as the most important data characteristic in comparison to 20% of Finance organisations.

Differences were identified between AI leaders and laggards. AI leaders see Interoperability as an important data characteristic compared with AI laggards. 15% of AI leaders said Interoperability is the most important data characteristic compared with 1% of AI laggards.

Further analysis and breakdown of most important data characteristic by organisational characteristics are provided in Appendix D, Supplemental Analysis.

The survey asked respondents to select one data characteristic that was most important to their organisation's success

Figure 9 Most important data characteristic

Characteristic	Percentage
Quality	41%
Usability	14%
Accessibility	12%
Consistency	9%
Proper documentation	8%
Interoperability	8%
Timelines	7%
Other	1%
Security	0%

In the evidence review, we identified that larger and younger organisations are more likely to understand the importance of data.[7] However, our survey results found that there is no material difference in the perceived importance of data based on organisation size and age. This suggests that understanding the importance of data has become more widespread and is no longer focused in leading organisations. This is supported by findings from the stakeholder interviews, as many respondents mentioned that data initiatives became a priority within the last two to three years and that the COVID-19 pandemic further highlighted the importance of data foundations.

Based on the qualitative research, the more widespread understanding of the importance of data has led to increased demand and competition for staff with relevant data skills (including in the third sector), resulting in wage inflation for those with increasingly desirable data science and technology skills.

Although organisations appear to understand the importance of data, our interviews found no organisation that systematically measures improvements in their data, and it is therefore difficult to quantify the monetary value of data and return on investment reliably. A potential reason behind this was that data is seen as an enabler, and data improvements are often bundled in wider organisational transformations making it challenging to allocate benefits specifically to data. This results in organisations being unable to assess the effectiveness of data initiatives or prepare compelling business cases for investment, which may be limiting organisations investments in people with relevant data skills and the required technology infrastructure.

3.2 Adoption of data foundations and artificial intelligence

> " If there is no good data foundations, AI will not work. We need to fix our systems and underlying data before we can apply AI in a more systematic and meaningful way
>
> Large charity

These findings relate to the following specific research questions:

▶ How can the adoption and improvement of data foundations be measured?
▶ What value does the adoption and improvement of data foundations bring to private and third sector organisations?
▶ How does improvement in data foundations impact the adoption of AI?

3.2.1 Understanding of the term data foundations

To ensure the credibility of survey responses and input from the interviews, it was important to assess respondents' understanding of the term 'data foundations'. The National Data Strategy uses the term 'data foundations' to mean data that is:

▶ Fit for purpose
▶ Recorded in standardised formats on modern, future-proof systems
▶ Findable, accessible, interoperable and reusable (FAIR)

To address this research area, we asked survey participants an aided awareness question about how familiar they are with the data foundations definition. Through further survey questions and interviews, we were then able to draw conclusions and insights with respect to the adoption of data foundations and AI across the UK.

Our key findings in this area are summarised below:

▶ 75% of the respondents, when prompted and having been provided the definition of data foundations, stated that they were at least somewhat familiar with the term 'data foundations'.
▶ However, during the interviews, many organisations said that they did not know that the term 'data foundations' existed, but on learning about the definition they confirmed they were familiar with the principles behind it. Some interviewees understood data foundations more broadly, with their definitions encompassing other related concepts e.g., systems, processes and capabilities.
▶ Survey responses also suggested a varied level of familiarity with the definition of 'data foundations' by industry, sector, AI adoption, organisation size and age. Younger and large organisations, Finance and TMT businesses, private sector and AI leaders were typically more familiar with the term.
▶ 45% of third sector organisations and 38% of AI laggards were not familiar with the term 'data foundations', compared with 14% of private sector organisations and 3% of AI leaders.

[7] DataKindUK and Data Orchard (2017) Data Evolution Project Report

- The level of familiarity with data foundations varied between organisations of different sizes, sectors and industries. Large organisations and the private sector are relatively more familiar with the term than SMEs and the third sector. Organisations in the Finance and TMT industries appeared to have the most familiarity with the definition.
- The findings suggest there are differences in level of familiarity with the data foundations definition although the principles are well understood and there appears to be no single understanding of the term that is used by all organisations. This suggests that the definition of data foundations could be communicated more effectively to achieve a more consistent understanding of the term, which could help with future policy interventions' communications' strategy and further research regarding data foundations.

## Figure 10   Level of familiarity with data foundations concept

(Scale: 1=Not familiar; 3 = Somewhat familiar; 5=Very familiar)

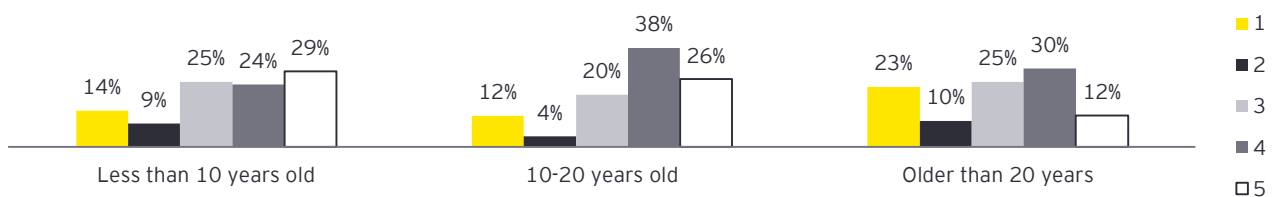| Familiarity with data foundations concept by industry					
Industry	1	2	3	4	5
CPR	14%	7%	21%	25%	32%
Finance	8%	4%	16%	32%	40%
Industrial	13%	6%	25%	40%	17%
Infrastructure	17%	11%	24%	27%	21%
Life Science	14%	14%	28%	28%	17%
Services	17%	9%	25%	28%	20%
Third sector	45%	8%	18%	20%	10%
TMT	7%	7%	25%	42%	18%
Total	17%	8%	24%	31%	21%

Familiarity with data foundations concept by sector
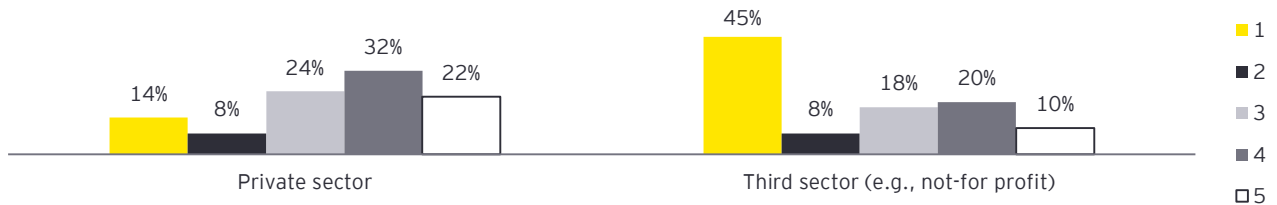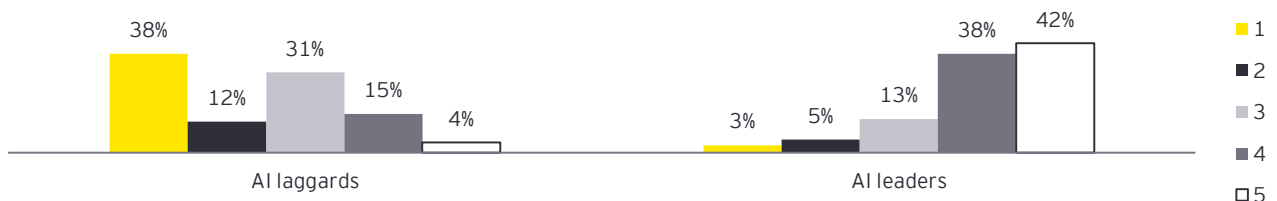

Familiarity with data foundations concept by organisation size
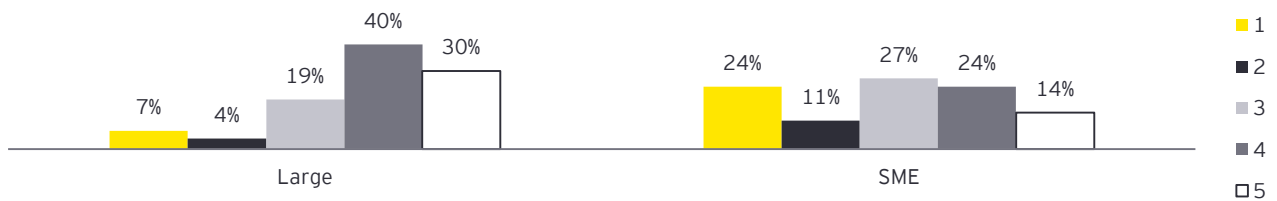
Familiarity with data foundations concept by organisation age

Familiarity with data foundations concept by AI adoption

Data foundations and AI adoption in the UK private and third sectors | 20

3.2.2 Adoption of data foundations

One of the National Data Strategy objectives is to ensure that appropriate data foundations are in place in organisations across the UK and to support the adoption of data-driven technologies such as AI. DCMS is committed to addressing market failures leading to data foundations being under-adopted or absent in the private and third sectors. To help identify potential drivers of market failure, we developed a composite measure of data foundations adoption (the **'Data Foundations Adoption score'**). This was calculated as the average (mean) of the scores from responses to questions about specific data characteristics such as Accessibility, Interoperability or Usability. Further details are provided in the Research Methodology section 2.2.4. The key findings from the analysis are:

► The average Data Foundations Adoption score was 4.0 (the score ranged from 1 to 5), signifying respondents on average agreed with the statements that their data is typically of required quality, consistent, accessible, properly documented, easily usable, interoperable, secure and timely. This suggests a relatively widespread level of data foundations adoption. Note that this is a relative measure; organisations were self-assessing and in the absence of any comparators, may not be aware of the 'best in class' potential within each of these categories.

► Interoperability (i.e. data that can be easily combined with other data sets and used across different systems) had the lowest average adoption score of 3.6. Interoperability and combining different datasets can provide significant value and lead to impactful business results. Organisations that use data in siloed ways will not be able to realise the full value of their data. There is a high level of complexity to achieving interoperability of data sources that are in different formats and from multiple systems. This could be contributing to the lower level of Data Foundations Adoption score.

► During the interviews, many respondents stated they have been making progress in data foundations, particularly over the last two to three years, but agreed that they are at the initial stages and their data journey has just started. Some organisations stated that they have advanced data foundations and that their focus now is ensuring data is used across their organisation and value is realised from the investment into data foundations.

► There were no material differences in the Data Foundations Adoption score by size of the organisation, region, age, AI adoption or industry. However, the level of data foundations adoption in the third sector was found to be relatively low compared with the private sector, which is consistent with the findings of our evidence assessment.[8] Interviews with third sector organisations indicated that they typically did not have sufficient resources to attract staff with relevant data skills (for which they are competing against the private sector) and that staff across the broader organisation and volunteers had limited data skills (e.g., older volunteers struggling to use applications effectively to capture customer data).

► When comparing large companies (>250 employees) that were less than 10 years old with large companies older than 20 years, there is a significant difference in the Data Foundations Adoption score. In older large companies the score was 3.9 compared with 4.4 for younger organisations.

► There was a weak but positive relationship between the Data Foundations Adoption score and the Perceived Value of Data score. Organisations with a higher Data Foundations Adoption score typically saw data as being more important (as measured by the Perceived Value of Data score) than organisations with a low Data Foundations Adoption score. However, differences in the Perceived Value of Data score were relatively minor, with 99% of survey participants stating that data is at least moderately important to their success (i.e., a Perceived Value of Data score of 3 and above).

Figure 11   Perceived Value of Data score compared with Data Foundations Adoption score
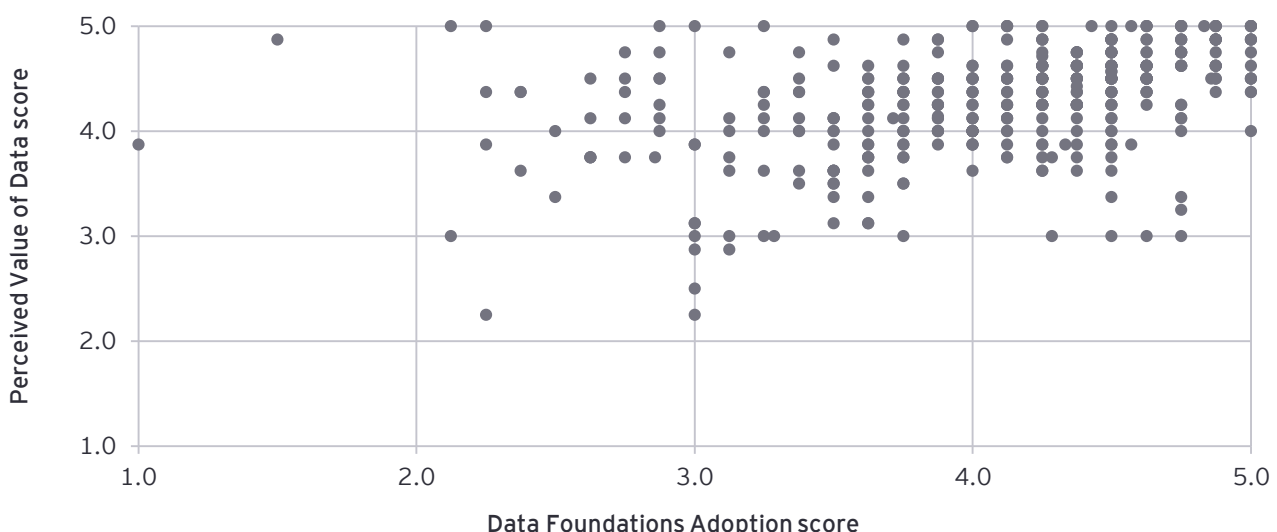
n = 399; some data points on the chart are overlapping

[8] Skills Platform, zoe amar digital (2020) Charity Digital Skills report 2020
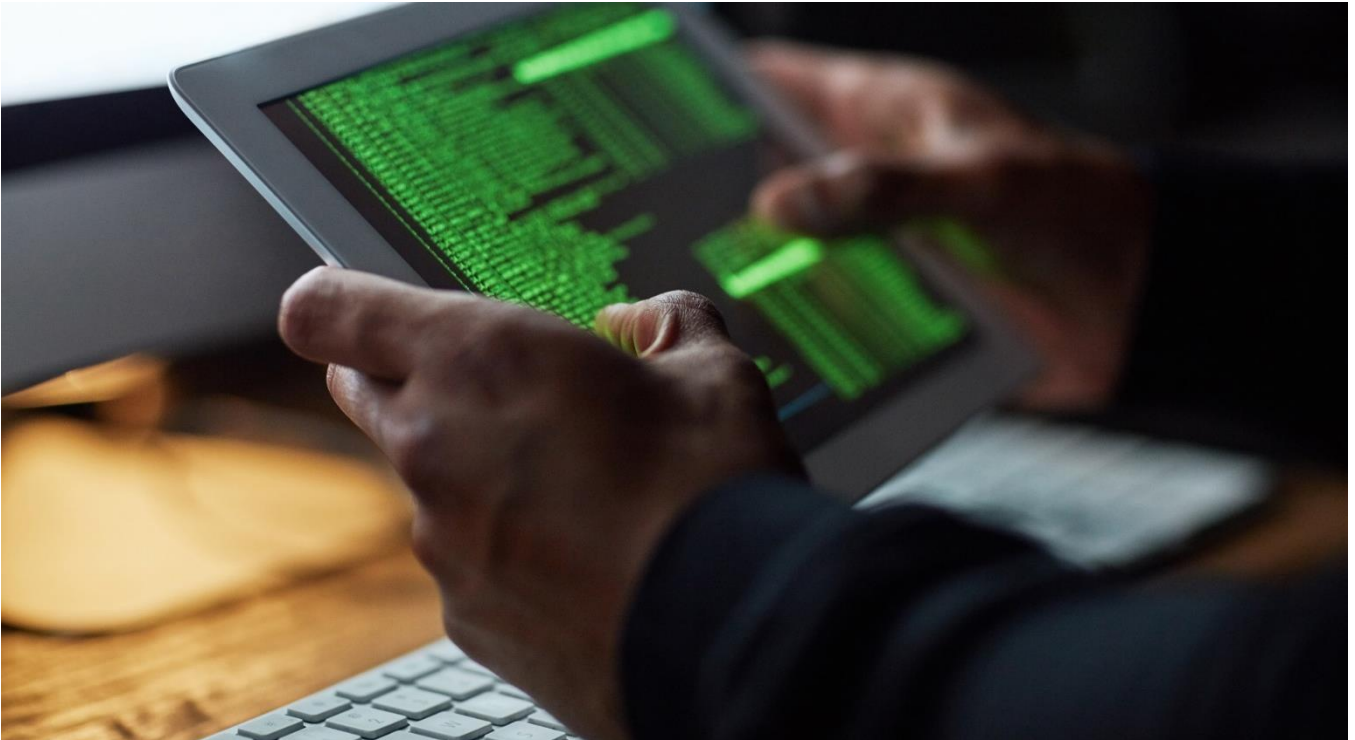
> **"**
>
> It is not always as easy to get data out of the data warehouse as it is to get data into it. Making data democratisation a reality is a focus of ours
>
> Large engineering company

> **"**
>
> We are a growing company, we are getting to a point where we are very interested in doing more with our data
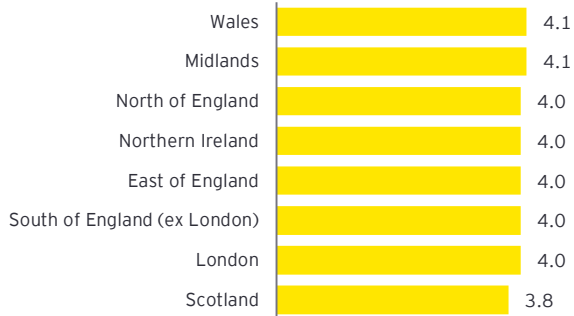>
> Small infrastructure company

> **"**
>
> We are fairly early on in our data journey. We have a few data products, but we could do so much more and there is much more potential in this space
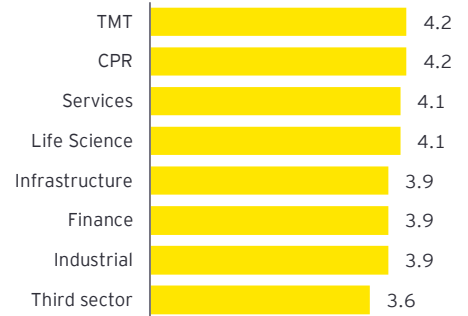>
> Large Financial Services organisation

Figure 12   Data Foundations Adoption score by key organisational characteristics
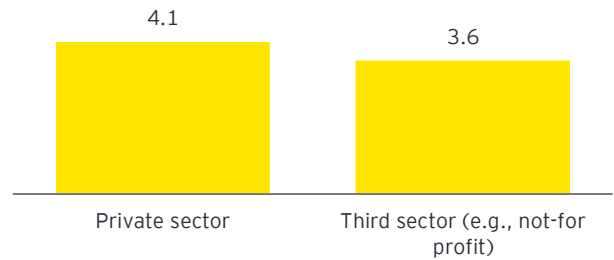
Data Foundations Adoption score by region

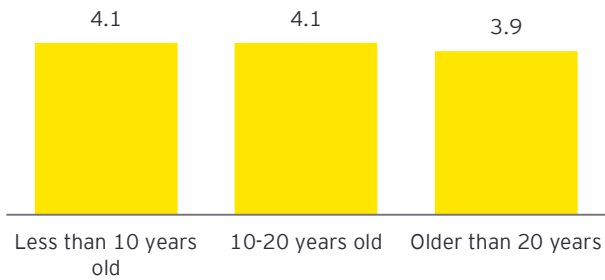| Region	Score
Wales	4.1
Midlands	4.1
North of England	4.0
Northern Ireland	4.0
East of England	4.0
South of England (ex London)	4.0
London	4.0
Scotland	3.8

Data Foundations Adoption score by industry

Industry	Score
TMT	4.2
CPR	4.2
Services	4.1
Life Science	4.1
Infrastructure	3.9
Finance	3.9
Industrial	3.9
Third sector	3.6

Data Foundations Adoption score by organisation size

Large	SME
4.1	4.0

Data Foundations Adoption score by sector

Private sector	Third sector (e.g., not-for profit)
4.1	3.6

Data Foundations Adoption score by organisation age

Less than 10 years old	10-20 years old	Older than 20 years
4.1	4.1	3.9

Data Foundations Adoption score by AI adoption

AI leaders	AI laggards
4.2	4.0
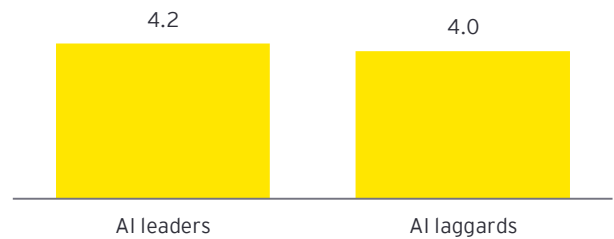
Data Foundations Adoption score by individual data characteristic

Accessible	Consistent	Easily usable	Interoperable	Of sufficient quality	Properly documented	Secure	Timely
4.2	4.1	4.0	3.6	4.0	4.0	4.3	4.0
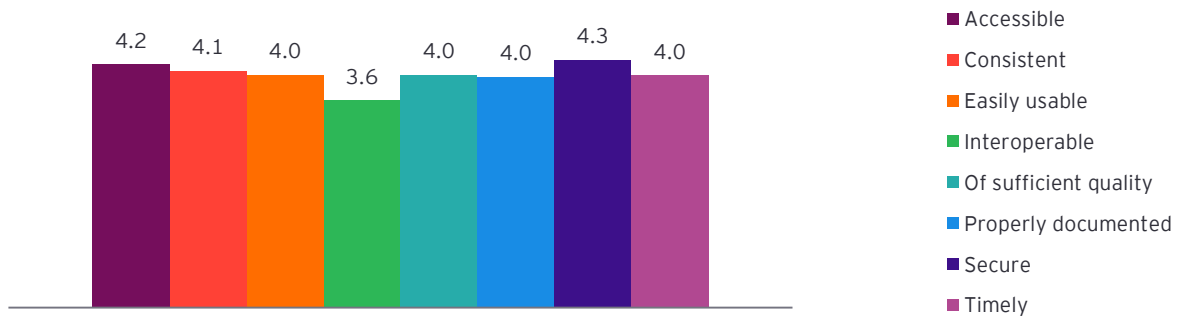
3.2.3 Benefits delivered by adopting and improving data foundations

Given that the importance of data is now widely understood and data foundations are widely adopted across all sectors, our research looked to understand the benefits that organisations can expect to receive from investments in data.

To analyse the benefits delivered by adopting and improving data foundations, we asked survey participants to indicate the level of impact (ranging from no impact to transformational) that an improvement in data foundations would have on various areas of the organisation, including revenue generation, employment generation, costs or deployment of AI. This was further investigated during interviews.

Our key findings in this area are summarised below:

► Organisations see improvement in data foundations as a significant value opportunity and expect wide-ranging benefits. This includes increased productivity (80% of respondents), revenue generation (75% of respondents), and customer engagement (72% of respondents), with 80% of respondents stating the impact in these three areas will range from moderate to transformational. Please refer to Figure 13 for further details and the full list of possible responses presented to survey participants are presented in Appendix A, survey question 6.

► The greatest benefits from improved data foundations (as measured by the Improving Data Foundations Impact score) are expected to be experienced by the Life Science industry, followed by Finance industry. Services and Infrastructure industries seem to expect to realise relatively lower benefits from improved data foundations. Large organisations and AI leaders are expected to realise greater benefits from improved data foundations than SMEs and AI laggards. There were no material differences in the Improving Data Foundations Impact score between organisations from different sectors or different ages. Further details are provided in section 3.3.2

► Qualitative analysis indicated that improved data foundations would increase productivity and reduce costs through reducing errors in data that would otherwise result in manual interventions, supporting process automation and 'democratisation' of data (enabling quicker analysis and decision making across the organisation), reducing time to find data, and providing management with greater visibility to manage performance.

► The qualitative analysis also indicated that data foundations could improve revenue generation by enabling better pricing decisions or improving customer retention and acquisition (e.g., understanding customer behaviours and requirements better).

► Developing new data-led business models and products was a lower priority for organisations.

► 92% of organisations that have a relatively high Data Foundations Adoption score (i.e., greater than 4.5, on a scale of 1 to 5) have a data strategy or data-related initiatives (in comparison with 77% of organisations with a relatively low score, i.e., below 3.0). The data strategies and data initiatives of organisations that have a high Data Foundations Adoption score focus more on improving data protection (61% vs 48%), data monetisation (32% vs 19%), supporting the deployment of AI (28% vs 13%) and other technologies (29% vs 19%).

► In comparison to organisations with low Data Foundations Adoption score, organisations with a high score expect to realise value from their data strategy more often through productivity improvements (68% vs 51%), revenue generation through new markets (34% vs 19%), and supporting deployment of AI (22% vs 8%) and other data-driven technologies (29% vs 16%).

► Some 44% of respondents stated that improvement in data foundations will have a positive impact on employment generation, while 58% stated that it will also result in increased employee engagement. This suggests that improving data foundations would have a net positive effect on job creation and job satisfaction.

► The deployment of AI is the least frequently identified area of impact of data foundations improvement (37% of respondents). There were material differences between industry (e.g., 52% of Finance organisations' strategy had a focus on AI vs 18% of CPR respondents) and organisation size (40% large vs 17% SMEs) and sector (28% private vs 10% third Sector). The question on the impact of data foundations on AI also had the highest level of 'don't know' responses which indicates uncertainty. This may highlight a potential misunderstanding of how AI can be used to achieve organisational objectives and the perception of AI as a goal in-and-of itself rather than a means to achieving a business objective.

► During our interviews, we found that some organisations were infrequently using AI capabilities available in off-the-shelf packages (e.g., Salesforce) to support selected processes but have not identified this in the survey as using AI. In some instances, respondents were not certain if AI was being used in their organisation, suggesting some organisations are not fully aware of what AI is or when it is being used. Therefore, some organisations may not fully understand the complications and risks associated with AI technology. Different approaches may be required to assess the adoption of AI when it is included in off-the-shelf tools.

► When AI solutions are packaged in off-the-shelf tools, and there is less understanding of how it works in a particular situation, there may be implications for ethics, regulation and responsibility for decision-making.

► Some 47% of respondents noted a positive impact on other data-driven technologies, suggesting that improvement in data foundations will support not only the adoption of AI but also the adoption of other technologies.

> " Data insights and analytics is a top priority, to try and get our organisation making more data driven decisions
> Large charity

Figure 13 Impact of improving data foundations by business area at an overall level

Legend: Positive impact · No impact · Negative impact · Don't know
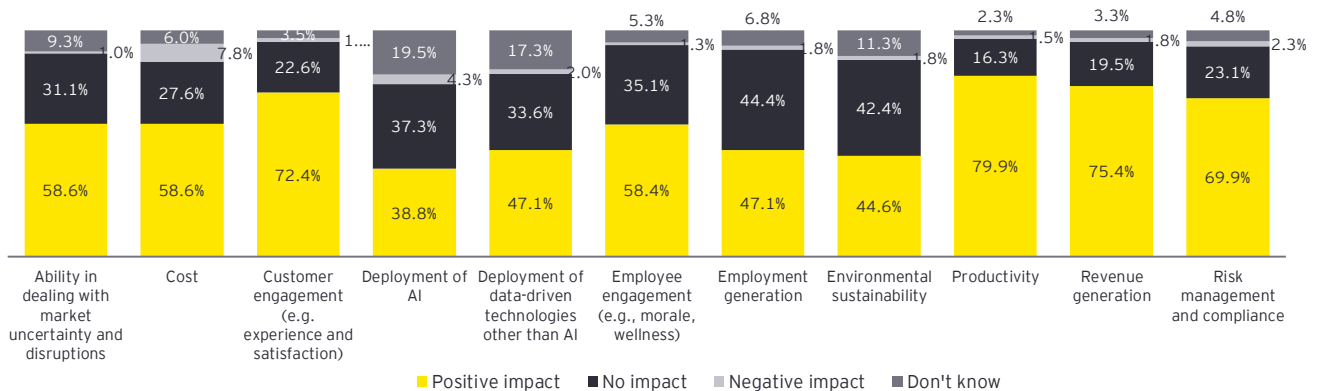
3.2.4 Impact of improvement in data foundations on adoption of AI

'Unleashing the transformational power of tech and AI' is one of the UK Government's Ten Tech Priorities.[9] AI has the potential to deliver significant benefits to the UK, but these benefits are unlikely to be realised without addressing barriers to AI adoption, which include: low data quality and availability, a lack of data infrastructure, and a lack of appropriate mechanisms and regulation for responsible data sharing.

Given the potential importance of AI to the future UK economy, this study has also considered the impact of improved data foundations on the adoption of AI. To do this, we analysed respondents' AI Adoption Level against their Data Foundations Adoption score, analysed to what extent data strategies focus on supporting the adoption of AI and supplemented this analysis with specific discussions around AI in the targeted interview programme.

Our key findings in this area are summarised below:

► Figure 14 shows there is no direct relationship between the AI Adoption Level and Data Foundations Adoption score. Organisations with high data foundations adoption are not necessarily reporting using AI or planning to use it in the future. This implies that some organisations could be 'AI ready' but not taking advantage of the benefits AI can bring.

► However, companies that are reporting using AI typically also report higher data foundations adoption. This is consistent with findings from the interviews, where interviewees were of the view that data foundations are a critical prerequisite to being able to adopt AI effectively.

► Our research confirmed that data foundations alone are not sufficient for organisations to adopt AI effectively. Therefore, additional explanatory or causal variables that are relevant to increasing AI adoption need to be understood. Our qualitative analysis identified the importance of skills development, increased trust in AI outputs and improved regulatory framework (in particular, in the Life Science industry) as factors in increasing AI adoption.

► Interoperability of data is an important factor for organisations with high AI adoption. When analysing companies that answered 'None' to AI adoption, they scored Interoperability of data at 3.6 for Large organisations and 3.5 for SMEs. Those organisations that answered 'Released' or 'Advanced' to the AI adoption question scored themselves 4.2 and 4.0 for Large and SME organisations, respectively. This data characteristic has the biggest change when comparing answers based on AI adoption.

► Figure 14 maps respondents' assessment of their Data Foundations Adoption score against AI Adoption Level. This clearly shows that whilst all organisations that claim they have high AI adoption also have high data foundations adoption, not all organisations with high data foundations adoption have high AI adoption. This analysis indicates that data foundations alone will not be sufficient to drive AI adoption across the UK, and additional intervention and policy support will likely be required. Although this analysis suggests data foundations are necessary but not a sufficient condition for high AI adoption, further research should be conducted in this area to determine the AI adoption pathway of these organisations. It may be the case that there is a time lag between the adoption of data foundations and the adoption of AI.

> "
> AI technology works well as far as there are defined data sets and there is accuracy in the data
>
> Large hospitality business

[9] https://dcms.shorthandstories.com/Our-Ten-Tech-Priorities/index.html

n = 399; some data points on the chart are overlapping

> " I would put data foundations on an equal footing with skilled resource who are able to utilise data foundations, infrastructure to make use of data foundations, and business adoption of the outputs of data foundations and AI techniques
>
> Large health club chain
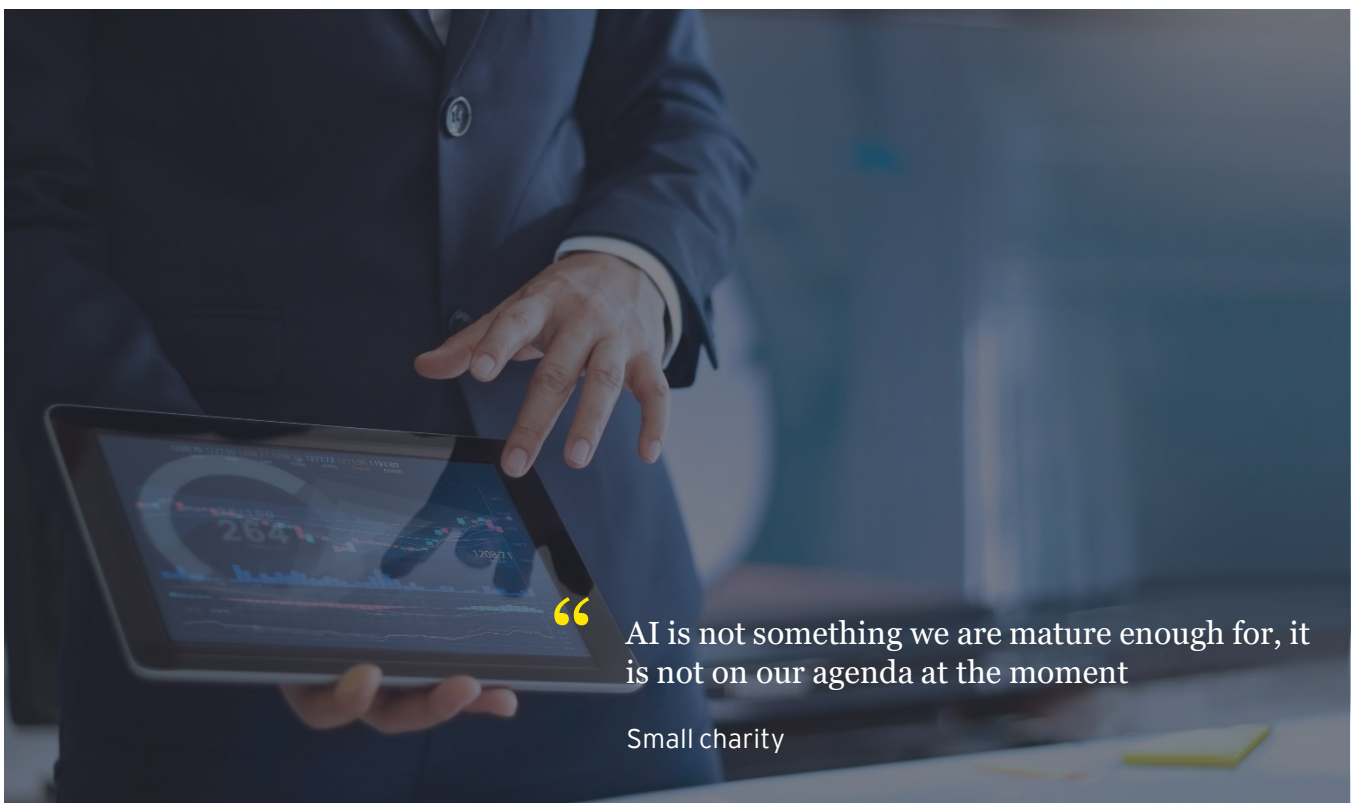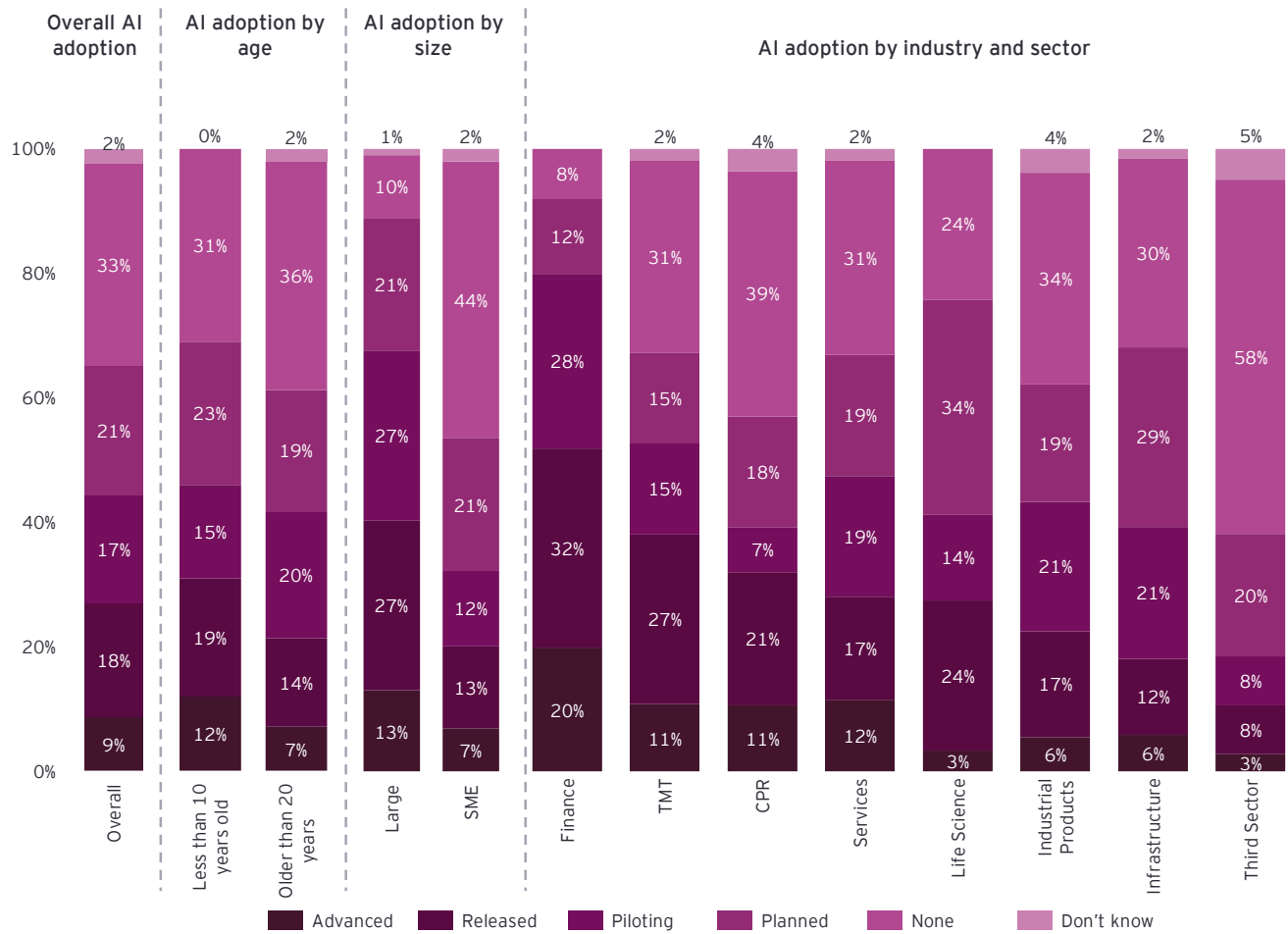
3.2.5 Adoption of AI across the UK economy

As part of this study, we have sought to understand the levels of AI adoption across the UK economy and identify whether this varies by organisational characteristics (e.g., location, size, sector and industry). This has included analysis of responses to specific questions in the survey, supplemented by discussions in the follow-up interviews and comparison with results from a European AI adoption survey.

Our key findings in this area are summarised below:

► AI remains an emerging technology with 27% of organisations at Released and Advanced level; 38% of organisations planning and piloting the technology; and 33% of organisations neither having adopted AI nor planning to.

► In comparison to AI laggards, data strategies and initiatives of AI leaders see an increased focus on data quality (68% vs 52%), data sharing and usage (57% vs 25%), and supporting deployment of AI and other data-driven technologies. AI leaders use AI more frequently across every business function, in particular in IT, Strategy and HR, and to automate and generate insights. AI leaders expect their data strategies and initiatives to deliver value mainly by increasing productivity (63% of respondents), reducing costs (51%), generating revenue through new products and services (47%) and entering new markets (47%). Further analysis of expected benefits of data strategies and initiatives is provided in Appendix D, Supplemental Analysis.

► AI Adoption Level is significantly higher in the private sector, with 70% of private sector organisations planning to use or already using AI, which compares with 42% in the third sector. Our interviews confirmed that AI is not often used in the third sector. Only one interviewed charity is currently using AI (to improve customer profiling and enhance customer experience) and believed this gives the organisation a competitive advantage due to the low adoption of AI in the third sector.

► Within the private sector, the size of organisation is a significant driver of AI adoption. Some 90% of large organisations confirmed they had already adopted AI or planned to do so, but this dropped to 48% for SMEs, which suggests the potential benefits of AI may not be equitably distributed across different sizes of organisation in the economy. This finding is consistent with what we have seen in our work with clients in the UK market outside of this study. AI's current application is often limited to automating repetitive tasks many times over, which are typically more common in larger organisations that have many standardised processes run multiple times a day, week or month. Many SMEs will not have a sufficient volume of standardised tasks drawn from the analysis of single or various datasets, and therefore will typically have fewer AI use cases than larger, more complex organisations. Consequently, it is harder for SMEs to identify opportunities for AI in their organisation, and when they do, to realise sufficient benefits to reflect the cost and perceived risks of implementing AI.

► Large UK organisations currently appear to be at a similar or more advanced AI Adoption Level as large European organisations in 2018, as per the AI adoption survey conducted by EY and Microsoft in 2018 across 269 large organisations in 15 European markets.[10] This research used standardised questions on the adoption of AI in order to compare responses with the EY and Microsoft study, but there is a limitation due to the timing difference between the reports.

► From an industry perspective, organisations operating in Finance and TMT report the highest AI Adoption Level, with 52% of respondents from the Finance industry and 38% from the TMT industry being at the Released or Advanced level. This could be due to these organisations tending to have more data-driven business models, being more technology-enabled and potentially having increased access to workforce with relevant data skills. Further analysis is required to understand the reasons behind this.

► Conversely, the Infrastructure and Industrial Products industries both show a lower AI Adoption Level with few organisations at an Advanced stage. However, with circa 40% of organisations at the Piloting or Released stage, both these sectors appear to be at least considering the potential for AI and at the early stages of implementation.

► Companies less than 10 years old were more likely to have Released or Advanced AI adoption (41%) than those more than 20 years old (33%). This difference is even more pronounced in large organisations, 55% vs 30%.

► 80% of AI leaders plan to increase or significantly increase investment in AI, compared with 45% of AI laggards. This could lead to a widening of the gap between these organisations. Further analysis of the planned change in investments in AI over the next three years is included in Appendix D, Supplemental Analysis.

[10] Artificial Intelligence in Europe, EY and Microsoft (2018)

Figure 15   AI adoption responses overall, by organisation age, size, industry and sector

Overall AI adoption

Segment	%
Don't know	2%
None	33%
Planned	21%
Piloting	17%
Released	18%
Advanced	9%

AI adoption by age

Segment	Less than 10 years old	Older than 20 years
Don't know	0%	2%
None	31%	36%
Planned	23%	19%
Piloting	15%	20%
Released	19%	14%
Advanced	12%	7%

AI adoption by size

Segment	Large	SME
Don't know	1%	2%
None	10%	44%
Planned	21%	21%
Piloting	27%	12%
Released	27%	13%
Advanced	13%	7%

AI adoption by industry and sector

Segment	Finance	TMT	CPR	Services	Life Science	Industrial Products	Infrastructure	Third Sector
Don't know		2%	4%	2%		4%	2%	5%
None	8%	31%	39%	31%	24%	34%	30%	58%
Planned	12%	15%	18%	19%	34%	19%	29%	20%
Piloting	28%	15%	7%	19%	14%	21%	21%	8%
Released	32%	27%	21%	17%	24%	17%	12%	8%
Advanced	20%	11%	11%	12%	3%	6%	6%	3%

Legend: Advanced · Released · Piloting · Planned · None · Don't know

" AI is not something we are mature enough for, it is not on our agenda at the moment

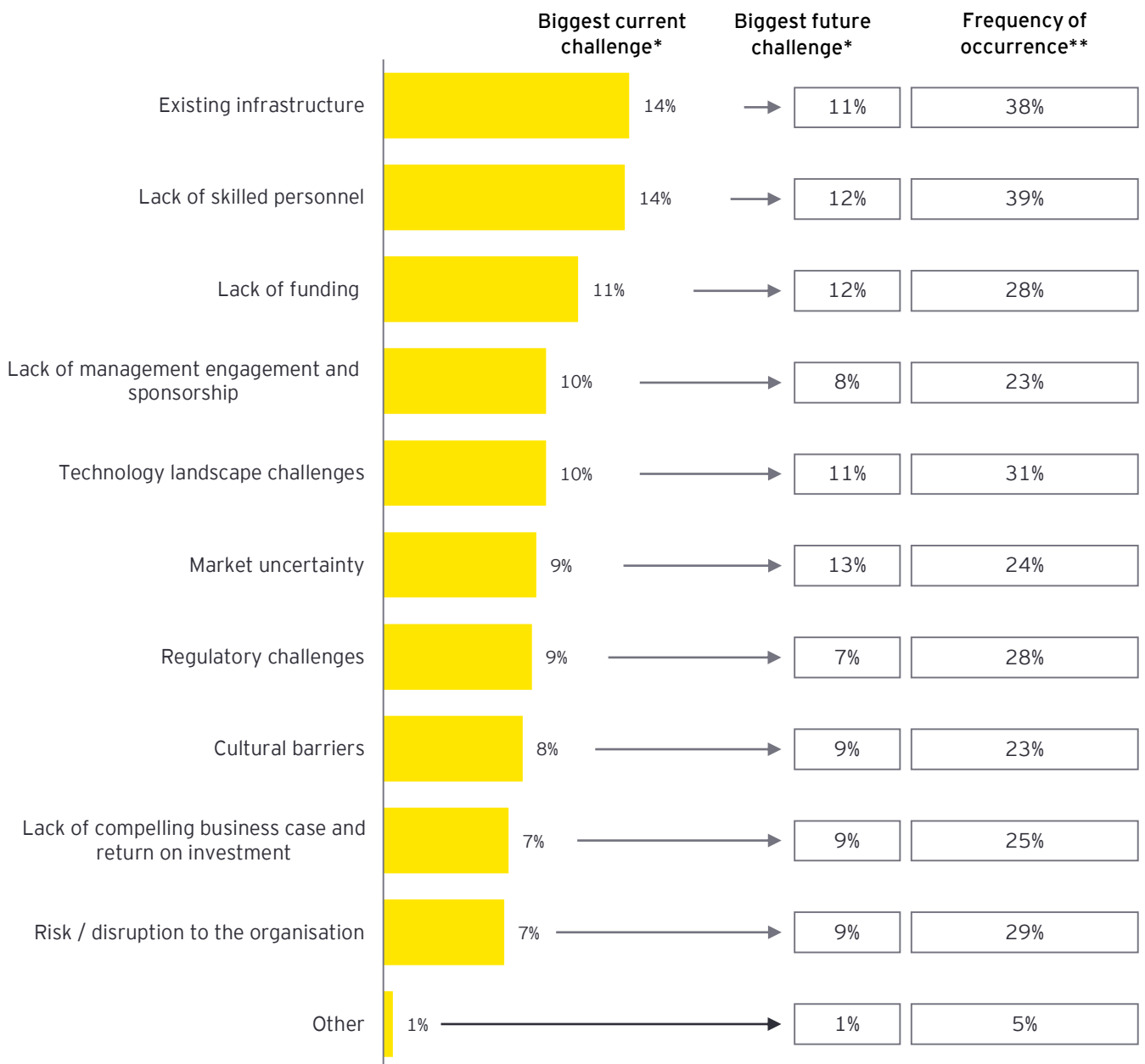Small charity

3.3 Barriers to adoption of data foundations

These findings relate to the following specific research questions:

▶ What are the barriers or challenges preventing organisations in the private and third sectors from adopting or improving data foundations?

▶ Are there significant differences in barriers based on organisations' characteristics?

3.3.1 Barriers and challenges preventing organisations from adopting and improving data foundations

Respondents cited a variety of barriers to adopting and improving data foundations, as summarised in Figure 16 below. These challenges can be barriers for organisations at any stage of the organisations' adoption of data foundations

Figure 16 Current vs. Future barriers and challenges to Data Foundations adoption

	Biggest current challenge*	Biggest future challenge*	Frequency of occurrence**
Existing infrastructure	14%	11%	38%
Lack of skilled personnel	14%	12%	39%
Lack of funding	11%	12%	28%
Lack of management engagement and sponsorship	10%	8%	23%
Technology landscape challenges	10%	11%	31%
Market uncertainty	9%	13%	24%
Regulatory challenges	9%	7%	28%
Cultural barriers	8%	9%	23%
Lack of compelling business case and return on investment	7%	9%	25%
Risk / disruption to the organisation	7%	9%	29%
Other	1%	1%	5%

* Most **problematic challenge currently experienced and expected in the future (within the next 3 years)**

** **Percentage of respondents who experienced challenge when improving organisation's data foundations**

Our key findings in this area are summarised below:

► The most problematic current challenges to adopting or improving data foundations are due to a lack of skilled personnel (14% of respondents), existing infrastructure (14% of respondents), and lack of funding (11% of respondents).

► Organisations expect the most problematic future challenges (i.e., within three years) to include market uncertainty (13%), lack of skilled personnel (12%) and lack of funding (12%).

► Lack of skilled personnel and challenges with existing infrastructure were also the most common challenges to adopting or improving data foundations (39% and 38% of respondents, respectively).

Data skills barrier

► Based on our interviews, many organisations struggle to find people with the right data skills and need to offer inflated rewards to attract and retain data talent. This is a significant challenge for all organisations but is more pronounced for third sector entities, which often do not have the same level of resources available to compete for limited skilled personnel with the private sector.

► It was also noted that in many organisations, the current employees often demonstrate relatively low data and digital skills and therefore cannot use and analyse data effectively, suggesting the need of an upskilling programme for existing staff in many organisations.

► In our view, access to data talent is a significant barrier to increasing the adoption of data foundations. This is confirmed by the data in this study, many other research studies that have identified this digital skills gap, the first-hand evidence we have within our own organisation and from our work with clients across the UK. This is ultimately a consequence of the demand for advanced technical data engineering, data analysis, computer science and AI skills exceeding the supply of qualified and experienced talent with those skills. Furthermore, a combination of those deep technical skills with broader commercial and entrepreneurial expertise is even more scarce. Yet, this is the ideal joint skill set individuals need

to be able to identify real-world use cases in organisations for data foundations and then apply those skills to identify practical, commercial interventions that improve operational and financial performance. Consequently, there is significant wage inflation for the skills organisations need to increase data foundations adoption, making it hard for many organisations to afford those skills and see commercial payback on potential recruits.

► To overcome this key barrier and improve data foundations adoption, there needs to be a concerted effort to increase the number of school leavers and graduates who have developed advanced data science skills and support adults retraining/changing careers into data-related roles. As data-related technologies continue to develop and further impact our day-to-day lives and businesses, this will become even more important than it is today. Numerous studies have also identified the significant digital skills gap we face in the UK. The Learning and Work Institute identified[11]:

► The number of young people taking IT subjects at GCSE has dropped 40% since 2015.

► Some 70% of young people enter their workplace expecting employers to invest in teaching them digital skills on the job, but only 50% of employers can provide that training.

► Fewer than 50% of British employees are leaving full-time education with sufficient digital skills for the workplace, and 76% of employers reported this is hitting their profitability.

► It will be necessary to increase the supply of school leavers and graduates with advanced data science skills and define clear career paths for data science professionals in the market that are appealing to young people, especially young women. This will help increase supply of appropriately skilled staff, reduce wage inflation and make it more affordable for all businesses to access the skills they will require to improve data foundations adoption in the future.

> **"**
>
> I am extremely concerned that I won't be able to find the right skill set we require in the UK at the right price point, so we might have to look elsewhere
>
> Large health club chain

> **"**
>
> Good talent with advanced skill sets in this space is pretty hard to find and demand is probably going to outstrip supply for a significant period
>
> Infrastructure company

[11] Disconnected? Exploring the Digital Skills gap – 22 March 2021 Learning and Work Institute (https://learningandwork.org.uk/resources/research-and-reports/disconnected-exploring-the-digital-skills-gap/)

Infrastructure barrier

▶ The most common infrastructure issues were related to organisations operating disparate legacy technologies and data systems. Our qualitative analysis indicated that legacy systems were not always structured to facilitate advanced analytics and AI and will therefore require some level of future investment.

Funding challenge

▶ Lack of funding is also cited as one of the key challenges in improving data foundations, particularly in the third sector (23% of respondents). In our view, difficulties in quantifying and demonstrating tangible value and return on investment from improved data foundations, together with high costs of attracting and retaining staff with relevant data skills, contribute to limited investments in data.

Cultural barriers

▶ Cultural barriers and lack of management sponsorship and engagement were the least common challenges (23% of respondents), which suggests organisational focus shifting from winning internal buy-in and understanding the theoretical benefit of data foundations to practical implementation and demonstration of return on investment.

Regulatory landscape

▶ Although the regulatory landscape was not identified as a significant barrier to adoption and implementation of data foundations by survey respondents (cited as an issue by just 24% of respondents) nor seen as particularly problematic (9% of respondents), during interviews some organisations mentioned the high costs and complexity of complying with data protection requirements. They suggested that Government guidance in this area would be helpful.

Differences across organisational characteristics

▶ Material differences in barriers to adoption were identified between industries and the private and third sectors. This is summarised in Figure 17. The data suggests challenges to the adoption of data foundations are industry-dependent, and industry-specific interventions should be considered.

▶ Differences in barriers to adoption were also identified between organisations of different sizes, ages and AI adoption.

▶ In particular, the most problematic challenges for SMEs were lack of skilled personnel and funding, whereas existing infrastructure was the most problematic challenge for large organisations.

▶ AI leaders' most problematic challenges included technology landscape, lack of skilled personnel and existing infrastructure; for AI laggards, these were lack of funding, market uncertainty and lack of a compelling business case. Further details are provided in Appendix D, Supplemental Analysis
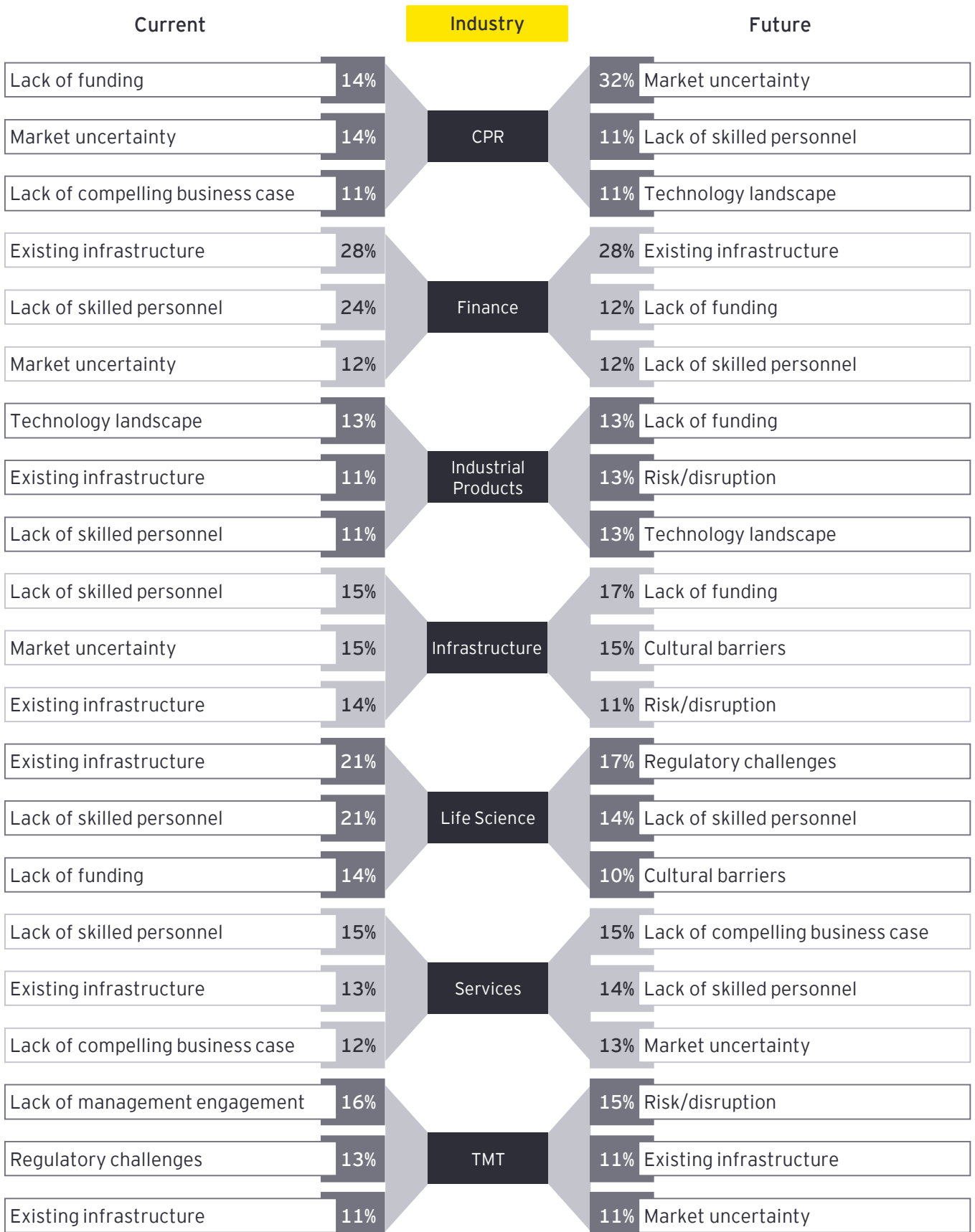

> **"**
> We have quite a few legacy systems, that work with our data and data processing. It is very tricky to persuade the business to dedicate resource to improving that ageing infrastructure
>
> Infrastructure company

Figure 17 Barriers and challenges preventing organisations from adopting and improving data foundations

Top three barriers and challenges by industry (current and future)

Current		Industry		Future
Lack of funding	14%		32%	Market uncertainty
Market uncertainty	14%	CPR	11%	Lack of skilled personnel
Lack of compelling business case	11%		11%	Technology landscape
Existing infrastructure	28%		28%	Existing infrastructure
Lack of skilled personnel	24%	Finance	12%	Lack of funding
Market uncertainty	12%		12%	Lack of skilled personnel
Technology landscape	13%		13%	Lack of funding
Existing infrastructure	11%	Industrial Products	13%	Risk/disruption
Lack of skilled personnel	11%		13%	Technology landscape
Lack of skilled personnel	15%		17%	Lack of funding
Market uncertainty	15%	Infrastructure	15%	Cultural barriers
Existing infrastructure	14%		11%	Risk/disruption
Existing infrastructure	21%		17%	Regulatory challenges
Lack of skilled personnel	21%	Life Science	14%	Lack of skilled personnel
Lack of funding	14%		10%	Cultural barriers
Lack of skilled personnel	15%		15%	Lack of compelling business case
Existing infrastructure	13%	Services	14%	Lack of skilled personnel
Lack of compelling business case	12%		13%	Market uncertainty
Lack of management engagement	16%		15%	Risk/disruption
Regulatory challenges	13%	TMT	11%	Existing infrastructure
Existing infrastructure	11%		11%	Market uncertainty

Barriers are also dependent on the level of adoption of data foundations, as shown below in Figure 18. The key challenges for organisations with relatively low data foundations adoption include a lack of skilled personnel and management buy-in. Organisations with relatively high levels of data foundations adoption faced challenges with existing technology infrastructure, risk of disruption to the organisation and regulation.

Figure 18   Barriers and challenges by data foundations adoption

Barriers and challenges	Low data foundations adoption*	High data foundations adoption*
Lack of skilled personnel	23%	11%
Existing infrastructure	20%	13%
Lack of management engagement and sponsorship	20%	7%
Lack of funding	13%	12%
Cultural barriers	7%	8%
Lack of compelling business case and return on investment	7%	7%
Regulatory challenges	3%	12%
Market uncertainty	3%	11%
Technology landscape challenges	3%	8%
Risk/disruption to the organisation	0%	12%

*Low data foundations adoption is defined as a Data Foundations Adoption score below 3. High data foundations adoption is defined as Data Foundations Adoption score greater than 4.5

3.3.2 Organisations with greatest benefit from improved data foundations

To help inform future data policy priorities and investments, we have analysed which industries could achieve the greatest benefit from improved data foundations.

The indicative impact of improved data foundations was estimated based on a single measure (the '**Improving Data Foundations Impact score**') calculated as the average (mean) of the scores from responses to questions about the level of data foundations impact on revenue generation, productivity, costs etc. (as detailed in 2.2.4 of the Research Methodology section).

The Improving Data Foundations Impact score was plotted on a 'bubble chart' against the Data Foundations Adoption score with each bubble's size indicating the industries' and sectors' share of UK GVA, i.e., the contribution made to the UK's economy. This approach allowed us to identify industries that may have the largest benefit from improved data foundations, whilst considering data foundations adoption and the potential impact to the UK economy.

Figure 19   Data Foundations Adoption score compared with Improving Data Foundations Impact score by industry and sector
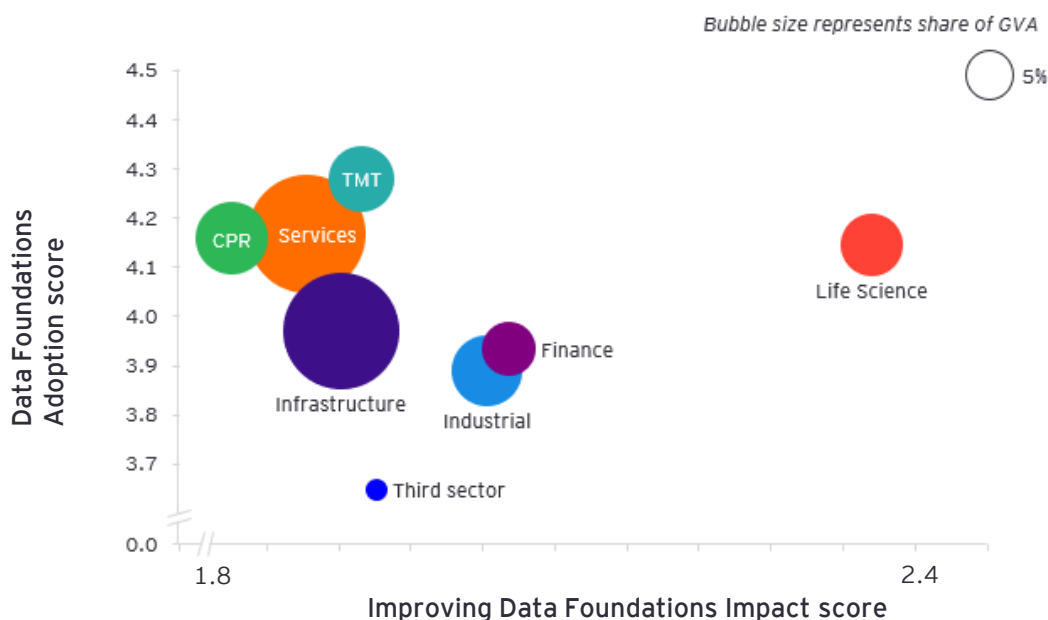
Our key findings in this area are summarised below:

► The greatest benefits from improved data foundations are expected to be experienced by the Life Science industry (Improving Data Foundations Impact score of 2.3), followed by Finance (score of 2.1). Further work should be undertaken to determine whether there are any lessons learned from these two industries that could be applied in other industries at a comparatively less mature stage of adoption.

► This finding is consistent with what we have seen in our work with clients in the UK market outside of this study:

  ► Life Sciences organisations have a particular interest in improved clinical, patient and genomic data, and data foundations. They can then derive insight from these datasets that support them and clinicians to identify which drug treatments are most likely to treat specific diseases in particular types of patient. This, in turn, would be expected to lead to advancements in personalised medicine, better health outcomes for citizens and improved value for money for taxpayers and life sciences companies. By unlocking the power of these combined datasets, clinicians can determine how to treat a particular patient more effectively rather than the patient's generic symptoms. Improved data and data foundations should also facilitate more efficient research and development activities for Life Sciences organisations, leading to a potential reduction in the cost of clinical trials and, ultimately, better outcomes for the patient, improved returns for the company and positive economic impact for the UK.

  ► Finance organisations can realise significant benefits from improvement in data foundations because they often have standardised processes that underpin core parts of their business (for example, processing account openings, mortgage applications, processing of compliance documents and regulatory returns). The nature of Finance organisations' businesses means they are often analysing structured, standardised datasets (for example, a customer application form) against a set of standard rules and doing so many times over. With strong data foundations, there is a greater opportunity for these businesses to adopt AI and other data-driven technologies across their business. We see this in many of our clients who are starting to use AI and automation to improve the speed, accuracy and efficiency of core business processes whilst also removing some of the more repetitive tasks and enabling employees to make better use of the higher-level skills they have.

► Services and Infrastructure industries are expected to realise relatively lower benefits from improved data foundations. However, these industries are the largest contributors to UK's economy and given their size, a relatively small positive change from improvement in data foundations may result in a material increase in UK's GVA.

► Broader considerations such as employment, socio-economic impact and wider Government strategic priorities should be considered when prioritising industries and sectors for data-related policy interventions. For example, the third sector has a small share of GVA but can generate a significant positive socio-economic impact on society and may therefore warrant greater focus than would be suggested if the only focus was GVA.

► Large organisations are expected to realise greater benefits from improved data foundations than SMEs (2.3 vs 1.8 Improving Data Foundations Impact score). AI leaders are also expected to realise greater benefits than AI laggards (2.2 vs 1.5 Improving Data Foundations Impact score). This suggests that organisations that are already using data-driven technologies such as AI stand to benefit the most from further improvements in their data.

► There were no material differences in the Improving Data Foundations Impact score between organisations from different sectors (score of 2.0 for the private and third sector) or of different age (score of 2.0 for organisations older than 20 years and 1.9 for organisations less than 10 years old).

"

The revenues we are making from data could be multiplied by a large factor over the next decade

Large Financial Services organisation

3.3.3 The importance of Government to support the adoption and improvement of data foundations

With the volume of data constantly growing and as economies become more digital, combined with the reduction in the cost of computing power, governments around the world are exploring how they can use data and technology to inform and drive better implementation of policy decisions, improved outcomes for citizens and value for money for taxpayers. Whether in the field of healthcare to improve patient outcomes, environmental protection to reduce pollution and carbon dioxide emissions, or education planning to determine future demand for schooling, governments all over the world are pursuing data initiatives to increase data availability for citizens and businesses and launching data programmes to encourage better collaboration between the private and public sectors in this area. Many governments are focused on encouraging the better use of data across their economies and can see the potential for data to deliver improved insights that can lead to better outcomes for their citizens. However, this is potentially sensitive given concerns around data ownership and privacy, so there is a need to build trust with all stakeholders (especially the public) and the private and public sector to work together for benefits to be realised.

Our key findings on the role of Government in increasing the adoption and improvement of data foundations are summarised below and in the following sections:

▶ Some 68% of respondents believe the Government has a role to play in helping organisations use data more effectively.

▶ 84% of AI leaders agreed or strongly agreed Government has a role in helping organisations use data more effectively (compared with 54% of AI laggards). AI leaders most frequently said the Government priorities should be investment in developing relevant data skills (79%), and improving and releasing datasets (47%).

▶ There were no material differences in views about the role of the Government by organisation age and sector. However, more large organisations and Finance businesses agreed that the Government has a role to play in supporting organisations to use data effectively (75% and 80%, respectively).

> **"**
>
> There is a real opportunity for Government to lead the way when it comes to access to data, open data and making use of things like data trusts. This could unlock huge change and innovation opportunities.
>
> Leading engineering firm
>
> **"**
>
> Government help in either upskilling or to incentivising different cohorts of the population to generate more skills or become more digitally upskilled would be welcome
>
> Large charity
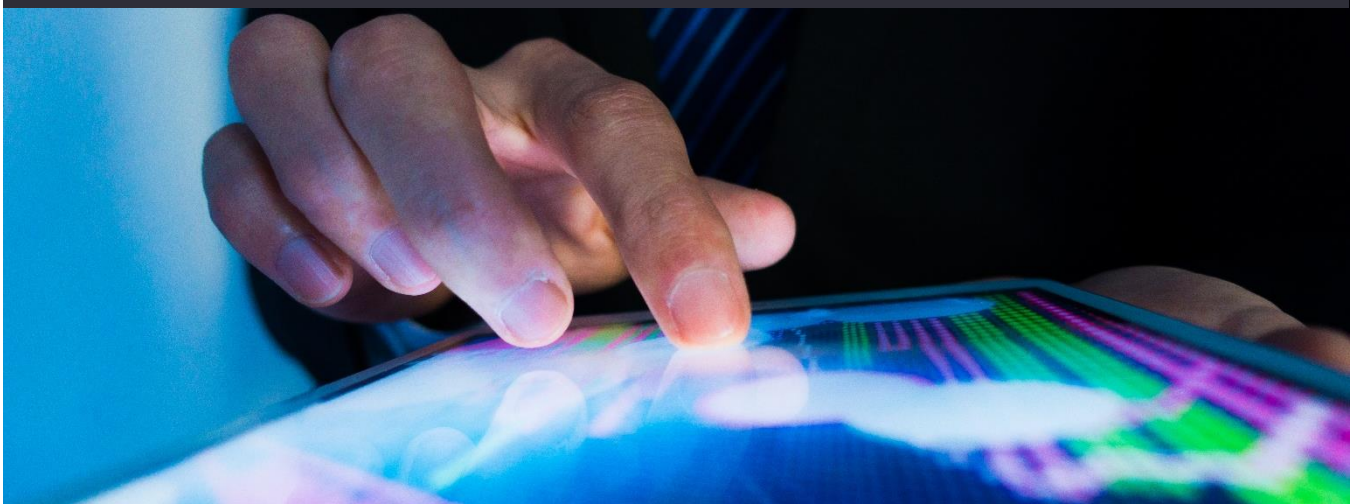
## Figure 20   Role of the Government

Respondents were asked whether the Government has a role to play in supporting the use of data effectively in the wider economy
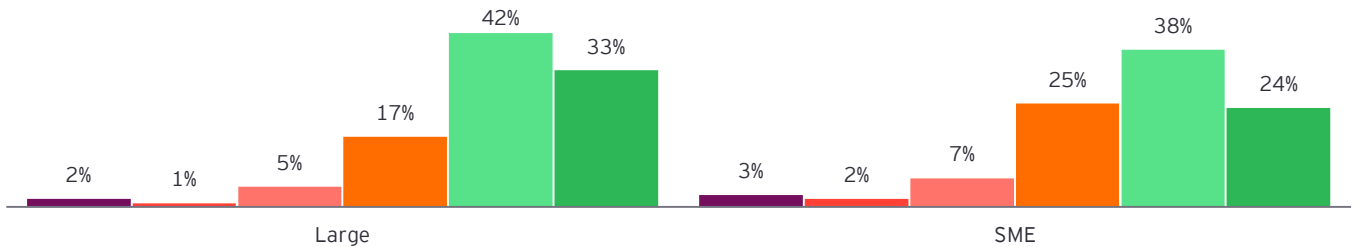
Role of Government in supporting use of data by industry

	Don't know	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
CPR	4%	–	4%	21%	50%	21%
Finance	–	–	8%	12%	32%	48%
Industrial	4%	4%	9%	21%	42%	21%
Infrastructure	4%	2%	3%	23%	45%	26%
Life Science	–	3%	7%	21%	38%	31%
Services	1%	1%	8%	27%	35%	28%
Third sector	10%	3%	3%	23%	43%	20%
TMT	4%	2%	5%	18%	38%	33%
Total	3%	3%	6%	22%	40%	28%

Role of Government in supporting use of data by sector
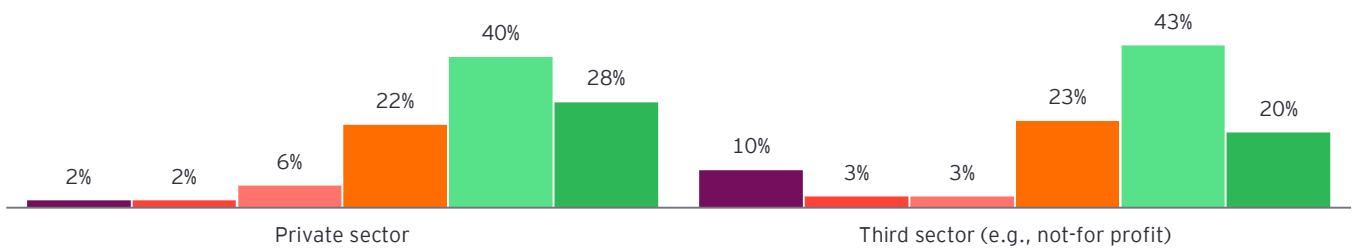
Role of Government in supporting use of data by organisation size

Role of Government in supporting use of data by organisation age
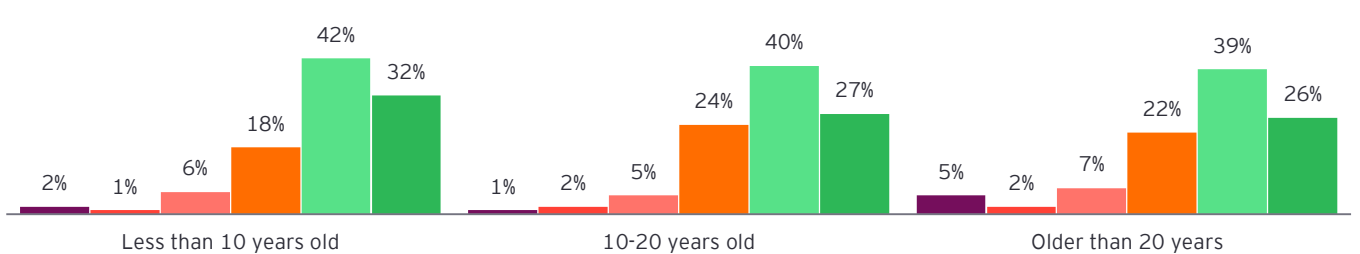
Role of Government in supporting use of data by AI adoption
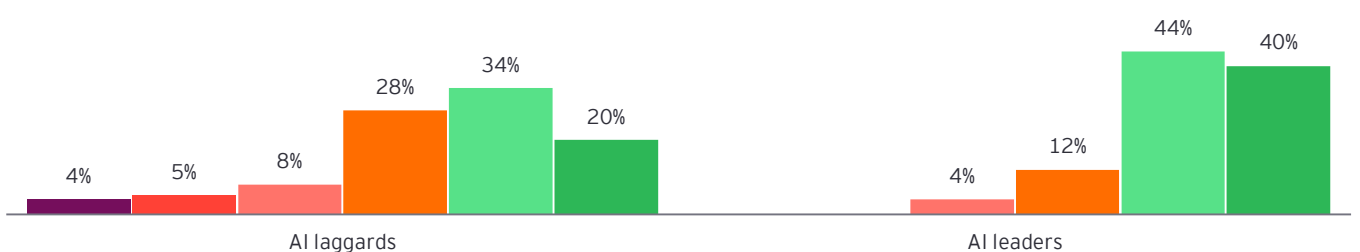
Legend: ■ Don't know ■ Strongly disagree ■ Disagree ■ Neither disagree nor agree ■ Agree ■ Strongly Agree

A weak, positive relationship was also found between the Perceived Value of Data score and views on the importance of the Government's role in supporting organisations to use data more effectively. Organisations with a high Perceived Value of Data score (i.e, above 4.75) more frequently identified the provision of funding, improving data-related regulatory framework and supporting the implementation of data standards as key areas for Government to address. Organisations with low Perceived Value of Data score (i.e., below 4.0) more frequently identified investments in improving and releasing data as a key Government priority. This may suggest these organisations may be less aware of the availability of public sector datasets and may have greater challenges with using them.

Figure 21   Perceived Value of Data score compared with percentage of respondents agreeing or strongly agreeing that Government has a role to play in supporting the effective use of data in the wider economy

Perceived Value of Data score	Government has a role in supporting use of data
Less than or equal to 3.5	35% agreed or strongly agreed
3.5 to 4.25	58% agreed or strongly agreed
Greater than or equal to 4.25	75% agreed or strongly agreed

"

I would love to see wider availability of data from the UK Government, with more centralised data sources and standardised data

Infrastructure company

"
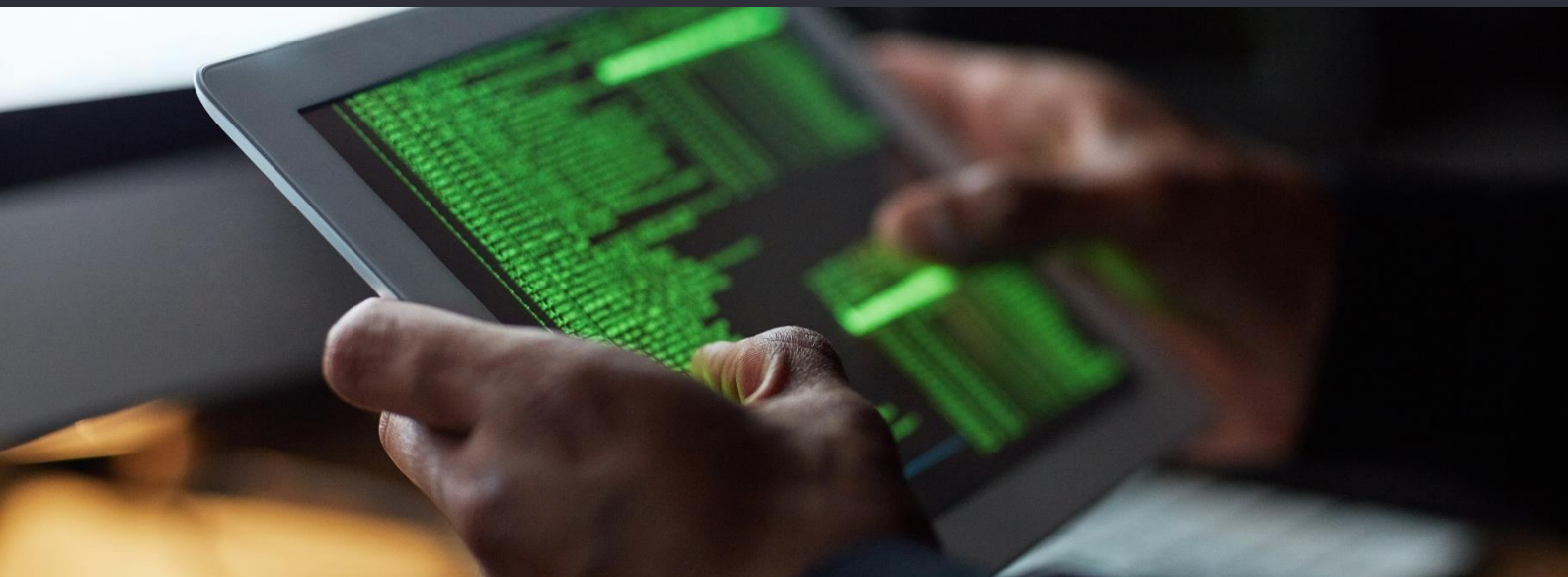
Fintech is a space where you need specific talent which is a pretty rare commodity, the UK Government should create a favourable environment to attract tech and data talent

Large Financial Services organisation

3.3.3 Role of Government in increasing the adoption and improvement of data foundations

▶ From a list of possible Government data-related interventions support, respondents' top three priorities to help organisations in private and third sectors use data more effectively were:

1. Investment in providing people with data skills and improving access to data talent (63% of respondents)

2. Providing funding to support effective use of data (38% of respondents)

3. Investment in improving and releasing datasets (37% respondents)

▶ These top priorities were common across all key organisational characteristics (industry, sector, size, age, AI adoption). Investment in developing data skills was the top priority for all organisation characteristics, apart from third sector organisations and AI laggards, which identified the provision of funding as the key Government priority (53% and 45% of respondents respectively). The top three Government priorities identified by survey respondents are presented in Figure 22 below.

Figure 22   Top three Government priorities by sector and organisation size

Top three Government priorities

Third sector: 53%, 48%, 38%
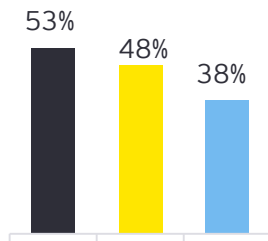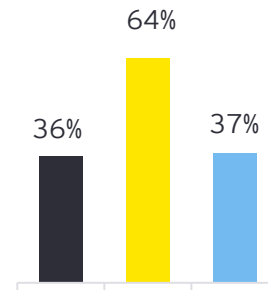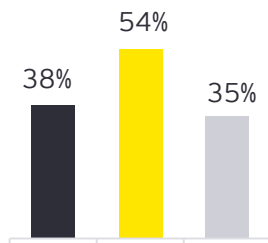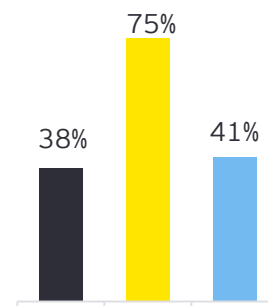
Private sector: 36%, 64%, 37%

SMEs: 38%, 54%, 35%

Large: 38%, 75%, 41%

Legend:
- Providing funding
- Investment in providing people with data skills and improving access to data talent
- Investment in improving and releasing datasets
- Supporting implementation of data standards

AI laggards

AI leaders

New organisations
(less than 10 years old)

Established organisations
(older than 20 years)

- Providing funding
- Investment in providing people with data skills and improving access to data talent
- Investment in improving and releasing datasets
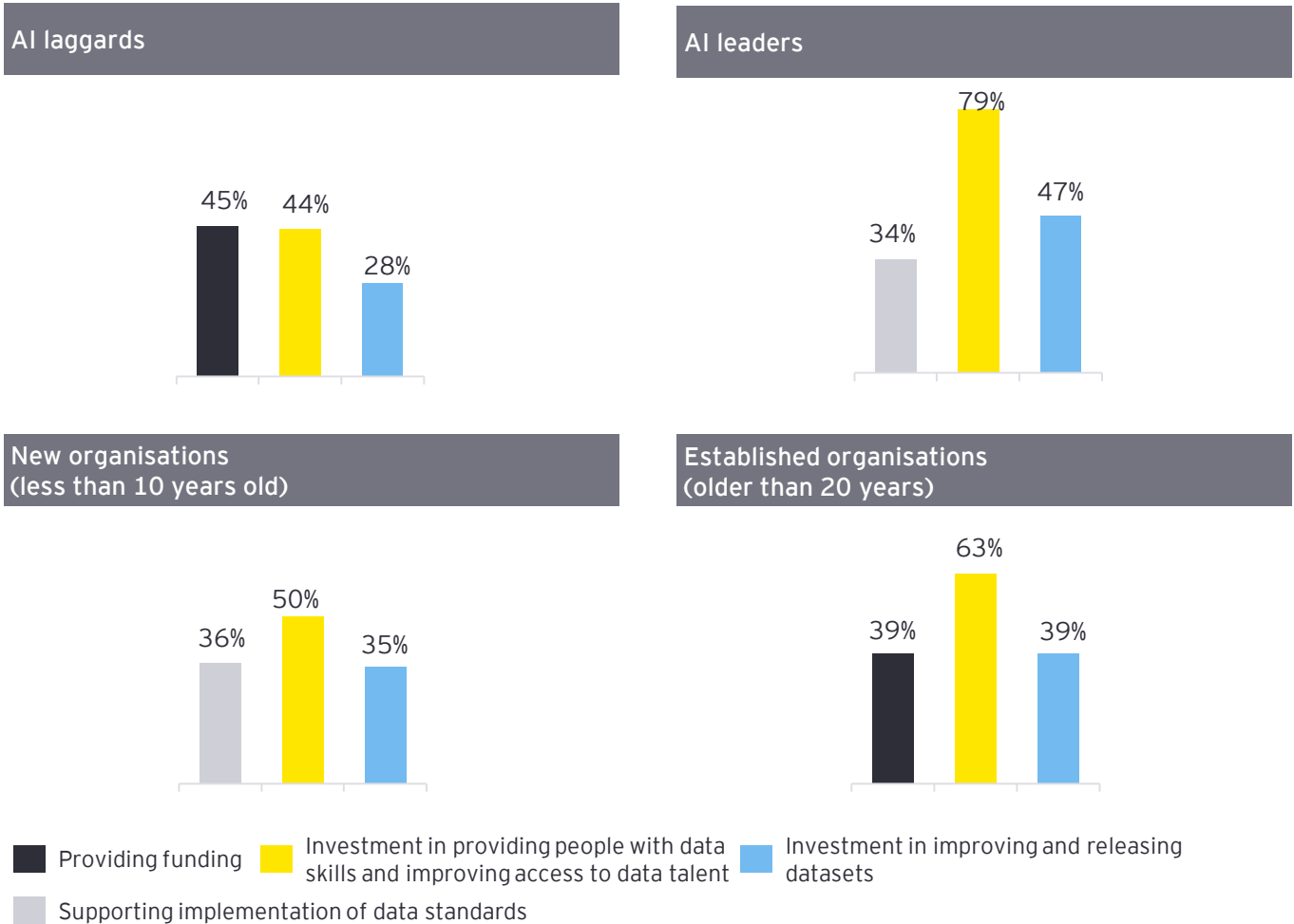- Supporting implementation of data standards

Figure 23 summarises Government priorities by data foundations adoption. Organisations that have a relatively high Data Foundations Adoption score identified the key Government data-related priorities as investment in data talent (62% of respondents), supporting implementation of data standards (42%) and improving data-related regulatory framework (31%). Organisations with a relatively low Data Foundations Adoption score identified the key Government priorities as funding (58%), investment in data talent development (55%) and investment in improving and releasing datasets (36%). These organisations identified improving the regulatory framework as less important. This is in line with our finding that regulation is not a significant barrier to improving data foundations for these organisations.

Figure 23   Government priorities by data foundations adoption

Government priorities	Low data foundations adoption*	High data foundations adoption*
Providing funding	58%	35%
Supporting access and investment in data talent development	55%	62%
Investment in improving and releasing datasets	36%	31%
Supporting implementation of data standards	35%	42%
Improving data-related regulatory framework	26%	36%
Information campaigns and increasing public awareness	23%	25%

*Low data foundations adoption is defined as a Data Foundations Adoption score below 3. High data foundations adoption is defined as Data Foundations Adoption score greater than 4.5

For each priority area, we address the considerations for Government below.

Talent development

Our work highlights that investment in data talent is considered the top priority for all private sector organisations, regardless of size. This is also the second-highest priority for third sector organisations. Such a strong and consistent response suggests investment in data talent development is the single most common data challenge currently faced by UK businesses and third sector organisations.

Therefore, the Government should consider policies and actions that will increase the availability of data-related skills, including data analytics, data management and governance and data engineering. The results from this study suggest that this will benefit all organisations across the economy. These policies and actions should cover both young people starting their careers and adults retraining/changing careers. Policies that support STEM-based subjects and develop data analytics skills leading to increased data talent availability should be considered as a priority. Various studies are evidencing the requirements for supporting the development of digital skills, including: 'No Longer Optional: Employer Demand for Digital Skills' and 'What digital skills do adults need to succeed in the workplace now and in the next 10 years?'.[12,13]

During interviews, SMEs and third sector organisations stated that recruiting and retaining staff with relevant data skills is very costly, indicating a direct link between lack of skilled personnel and lack of funding. Policies and actions to support these organisations could include increasing the supply of data talent to reduce talent costs and providing funding to support them in upskilling their workforce.

Providing funding

Lack of funding is considered the second highest barrier and could indicate a link with investment required to increase adoption of data foundations and also investment in human capital to bridge the skills gap. Further research into how the Government can support and encourage businesses to invest in their technology infrastructure and develop their human capital could address the two most fundamental challenges of business around the adoption of data foundations.

An option could be to provide Government funding to help and encourage organisations to kick-start data initiatives, as these may require a substantial investment. This investment can sometimes be difficult to justify given the challenges with quantifying the value of data and the impact of improving data foundations.

Improving and releasing datasets

The Government and public sector collect, generate and store huge amounts of data that is valuable to private and third sector organisations. Some 37% of respondents suggested that further investments in improving and releasing datasets should be a priority. Interviewees cited difficulties in finding, using and combining different public sector datasets. Our qualitative analysis further identified that the focus should be on enhancing existing datasets rather than investing in releasing new datasets. Some specific examples are included below:

► Improving awareness of the public sector data that is available

► Improving the findability, consistency (e.g., between local authorities or NHS trusts), usability (e.g., embedding analytics in datasets, file formats) and quality of public data

► Consolidating selected disparate datasets. One example provided during the interviews was creating a centralised warehouse with information from different public sector bodies relevant to real estate investment decisions.

Initiatives and policies supporting ease of access and ensuring completeness of datasets could act as an enabler for businesses to plan their growth and may have a broader impact on UK's economic growth and attractiveness as a commercial hub.

The Government also has a role to play in encouraging and supporting private and third sector organisations in make better use of data. This could include incentivising organisations to share data where there is a social benefit or improving access to data e.g., through exploring data trusts or data cooperatives. During our interviews one specific example was for the Government to provide enhanced support around the Construction Data Trust initiative.[14] This initiative was seen by the interviewee as a "mechanism that could unlock huge change and innovation opportunities in the construction sector as well as something that could be duplicated in other sectors and ultimately become a global differentiator for UK plc".

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[12] Department for Digital, Culture, Media and Sport (2019) No Longer Optional: Employer Demand for Digital Skills

[13] Warwick Institute for Employment Research (2018) What digital skills do adults need to succeed in the workplace now and in the next 10 years?

[14] http://www.datatrust.construction/

4 Key conclusions and considerations

This report provides insights into the extent to which organisations understand the value of data; the adoption of data foundations and AI by the private and third sector, the impact of improving data foundations, the barriers to improving data foundations and the role of Government in supporting the adoption and improvement of data foundations.

We found that organisations understand the potential value they can get from data and data analysis. Although data foundations (as defined by the National Data Strategy) appear relatively widespread, organisations are still at an early stage in their data improvement journey.

It is evident that businesses see the potential to derive insights from data for improved business performance as a significant opportunity. However, organisations are facing practical and technical implementation challenges, such as issues with existing infrastructure, lack of skills availability and a lack of initial funding.

Cultural challenges and buy-in from management are not deemed significant barriers, indicating a broad acceptance to the concept of 'data-driven decision-making', and an understanding of the crucial role data foundations would likely play in the future growth of our businesses, the broader UK economy and UK's standing as an attractive destination for inbound investments.

Government has a key role in tackling these challenges and helping organisations realise the full potential value of data for the benefit of the UK economy and for the UK to be the global leader in attracting international talent and business.

We found that AI is still an emerging technology with investments in AI planned to increase. To make the most of these investments, there are barriers that will need to be overcome. These barriers are discussed below.

4.1 Key considerations

The following considerations for Government are based on the findings from our market research and are positioned to tackle the barriers identified by organisations when adopting data foundations and AI:

► Address the shortage of data skills in the UK by providing conditions for developing data skills, incentivising new job market entrants to consider technology-focused careers and encouraging and supporting the experienced workforce to retrain and upskill to service the burgeoning demand.

► Encourage and incentivise the private and third sectors to invest in data infrastructure to address challenges with existing data and IT infrastructure. This may require further research to gain deeper understanding of the underlying issue, i.e., the requirement for additional funding vs prioritising investment in technical infrastructure through redeployment of existing funds.

► Continue investing in improving the quality, consistency, interoperability of data across the public sector and, where appropriate, consider sharing that data more broadly to enable the private sector, third sector and citizens to produce valuable insights. Consolidating selected disparate datasets (e.g., medical datasets) into a small number of secure, rich and accessible repositories would further support the adoption and improvement of data foundations in the UK economy.

► Continue developing initiatives and policies to improve access to and sharing of private sector data, e.g., through exploring data trusts or data cooperatives.

► Support collaboration between industries deemed to be leading in data foundations adoption (e.g., Finance, Life Sciences) and industries in the earlier stage of adoption (e.g., Infrastructure, Services) to encourage cross-industry sharing of data-related best practices and knowledge to drive an increase in overall data maturity.

4.1 Key considerations (continued)

► Data foundations are a necessary but not sufficient condition for the adoption and use of AI. Policies need to be specifically targeted at AI adoption and data foundations to help organisations increase their AI adoption. More holistic policies targeted at data foundations need to be considered to help organisations increase their AI adoption. Given the significant differences observed in barriers to adopting data foundations and AI across industries, industry-specific interventions should be considered. Further research to understand the data and AI adoption pathway could provide more detail in this area.

► In order to track progress over time, the improvement of data foundations should be measured through a regularly commissioned broad-scale survey to assess organisations' data foundations adoption. A standardised model to measure the 'absolute' value of data foundations should be considered, e.g., providing clear definitions of what is meant by different levels of data foundations adoption. This would enable an assessment of data foundations adoption on an absolute, rather than relative, level. In the meantime, relative measures that were developed as part of this project could be used, including: Perceived Value of Data score, Data Foundations Adoption score, Improving Data Foundations Impact score.

► Data is an increasingly valuable asset for businesses, not just technology-focused businesses as has been the case up until recently. As the valuation of businesses becomes more closely linked to the value of data that businesses hold, the Government should consider providing guidance on data valuation methodologies and consider supporting further research in this area. Such methodologies could be considered by businesses to measure their digitally-enabled value creation, which would be crucial for the future growth of the UK's digital economy.

► The findings relating to an increased adoption on data foundations and AI by younger companies show that there are some pioneering new, large companies in the UK that are adopting mature data practices and relatively advanced AI adoption. Further research is required to determine whether these companies have an 'AI-first' approach and therefore have invested in the data foundations or whether adoption of data foundations have enabled relatively easier implementation and release of AI in their business processes.

Appendices
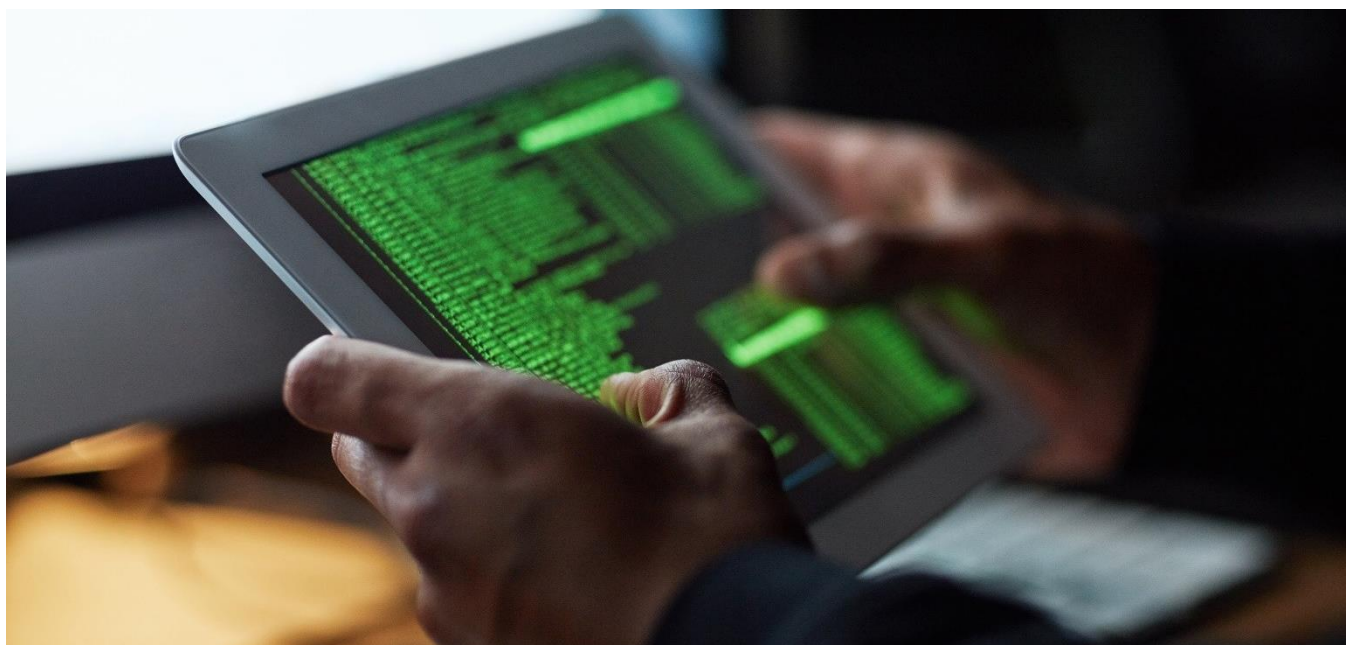
A Mapping of survey questions to research areas

Mapping is indicative, as survey questions were used to address multiple research areas

No.	Survey questions	Research area
1	How important are the following data characteristics to your organisation's success: quality, consistency, accessibility, appropriately documented, usability, interoperability, security, timeliness? Scale 1 – Not important, 5 – Critically important	Value of data: To what extent do private and third sector organisations understand the potential value of data? To what extent do they view data as a strategic asset? How do organisational characteristics influence organisations' perceived value of data?
2	Which of these data characteristics is most important to your organisation's success? Please select one: quality, consistency, accessibility, appropriately documented, usability, interoperability, security, timeliness	
3	What is the focus of your organisation's data strategy/data-related improvement initiatives? Please select all that apply: ► Enhancement of data collection ► Improvement in data quality, integrity and governance ► Improvement in data sharing and usage (e.g., application of data analytics and visualisation) ► Improvement in data to support deployment of Artificial Intelligence ► Improvement in data to support deployment of data driven technologies other than Artificial ► Intelligence (e.g., blockchain, Internet of Things, advanced data integration tools) ► Improvement in data protection (e.g., cybersecurity, privacy) ► Data monetisation (e.g., develop new business model to sell data, sell access to data or sell insights from data) ► We don't have a data strategy/data-related initiatives ► Other (please specify)	
4	What business benefit do you expect your data strategy/data-related improvement initiatives to generate? Please select all that apply: ► Business/revenue generation – new products and services ► Business/revenue generation – new markets (sector and/or geographic) ► Productivity Improvement (e.g., operational efficiencies) ► Cost reduction (e.g., enhanced decision-making) ► Support deployment of AI ► Support deployment of data-driven technologies other than AI ► Increased customer engagement (e.g., experience and satisfaction) ► Increased employee engagement (e.g., morale, reduced level of employee frustration) ► Risk management and compliance ► Improved environmental sustainability ► Greater ability in dealing with market uncertainty and disruptions ► Other (please specify)	

No.	Survey questions	Research area
5	How familiar are you with the term 'data foundations'? Scale 1 − Not familiar, 5 − Very familiar	2. Adoption of data foundations and Artificial Intelligence (AI): How can the adoption and improvement of data foundations be measured? What value does the adoption and improvement of data foundations bring to private and third sector organisations? How does improvement in data foundations impact the adoption of Artificial Intelligence?
6	Please indicate the impact (positive or negative) that an improvement in data foundations in your organisation would have on the following areas of your business within the next 3 years. Scale: 1 − minor, 5 − transformational ▶ Revenue generation ▶ Employment generation ▶ Productivity ▶ Cost ▶ Deployment of AI ▶ Deployment of data-driven technologies other than AI ▶ Customer engagement (e.g., experience and satisfaction) ▶ Employee engagement (e.g., morale, wellness) ▶ Risk management and compliance ▶ Environmental sustainability ▶ Ability in dealing with market uncertainty and disruptions	
7	How would you describe your organisation's general AI maturity? ▶ None (Not yet thinking about AI) ▶ Planned (AI is being planned but not yet put to active use, not even in early-stage pilots) ▶ Piloting (AI is put to active use but still only in early stage pilots) ▶ Released (AI is put to active use in one or a few processes in the company, but still quite selectively, and/or not enabling very advanced tasks) ▶ Advanced (AI is actively contributing to many processes in the company and is enabling quite advanced tasks)	
8	Are you planning to decrease or increase investments in AI over the next 3 years? Scale: 1 − significantly decrease, 5 − significantly increase	
9	Which business functions areas do you use AI in? Please select all that apply ▶ Strategy ▶ General Management ▶ Admin, Finance ▶ Product development and management ▶ Procurement ▶ Manufacturing ▶ Operations/Logistics ▶ IT/Technology/Digital ▶ Marketing ▶ Sales ▶ Customer service ▶ Other (please specify)	

Ref	Survey questions	Research area
10	How would you describe your company's AI maturity in those business functions? Scale: ▶ Planned (AI is being planned but not yet put to active use, not even in early stage pilots) ▶ Piloting (AI is put to active use but still only in early stage pilots) ▶ Released (AI is put to active use in one or a few processes in the company, but still quite selectively and/or not enabling very advanced tasks) ▶ Advanced (AI is actively contributing to many processes in the company and is enabling quite advanced tasks)	2. Adoption of data foundations and AI: How can the adoption and improvement of data foundations be measured? What value does the adoption and improvement of data foundations bring to private and third sector organisations? How does improvement in data foundations impact the adoption of AI?
11	What is AI currently used for in your organisation? Please select all that apply ▶ To predict (i.e., anticipate events and outcomes) ▶ To automate (i.e., handle tasks without human intervention) ▶ To generate insights (i.e., Identity and understand patterns and trends) ▶ To personalise (i.e., tailor content and user experience) ▶ To prescribe (i.e., suggest solutions to defined problems)	
12	How would you describe your company's AI maturity in those use cases? Scale: ▶ Planned (AI is being planned but not yet put to active use, not even in early stage pilots) ▶ Piloting (AI is put to active use but still only in early stage pilots) ▶ Released (AI is put to active use in one or a few processes in the company, but still quite selectively and/or not enabling very advanced tasks) ▶ Advanced (AI is actively contributing to many processes in the company and is enabling quite advanced tasks)	

Ref	Survey questions	Research area
13	Which of these challenges have you experienced when implementing initiatives to improve your organisation's data foundations? Please select all that apply ▶ Lack of skilled personnel ▶ Lack of management engagement and sponsorship (not a business priority) ▶ Lack of compelling business case and return on investment ▶ Market uncertainty (i.e., not a business priority due to ambiguity around market developments and future revenue streams) ▶ Cultural barriers (e.g., resistance to change, siloed working, limited collaboration across the organisation) ▶ Lack of funding for initial upfront investment required ▶ Regulatory challenges (e.g., regulatory complexity, uncertainty, data protection requirements) ▶ Technology landscape challenges (e.g., complexity and uncertainty of various data technologies) ▶ Risk/disruption to the organisation ▶ Existing infrastructure (e.g., complexity of legacy systems) ▶ Other (please specify)	3. Barriers to adoption: What are the barriers or challenges preventing organisations in the private and third sectors from adopting or improving data foundations? Are there significant differences in barriers based on organisational characteristics?
14	Which of these were most problematic/most difficult to deal with? Please select one Same response options as in Q13 were applied	
15	What do you see the key challenges being for any future initiatives to improve data foundations in your organisation (within next 3 years)? Please select all that apply Same response options as in Q13 were applied	
16	Which of these challenges do you think would be most problematic/difficult to deal with when implementing future data foundations improvement initiatives (within next 3 years)? Please select one Same response options as in Q13 were applied	
17	Does the Government have a role to play in supporting the use of data effectively in the wider economy? Scale 1 – strongly disagree, 5 – strongly agree	
18	What should the Government priorities be to help organisations in your sector use data more effectively? Please select up to top three priorities ▶ Providing funding (e.g., loans, grants, tax benefits) to support the effective use of data in organisations ▶ Improving data-related regulatory framework (including IP rights, industry specific regulations) ▶ Information campaigns and increasing public awareness of AI and data-driven technologies (e.g., sharing best practices) ▶ Improving regulation to improve access to data science talent ▶ Supporting implementation of data standards ▶ Investment in improving and releasing datasets ▶ Investment in data talent development ▶ Other (please specify)	

B Grouping of industries for reporting purposes

For reporting purposes, we grouped similar industries together by SIC code for higher sample sizes.

SIC code	Key SIC code industries	Grouping
G	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	CPR
K	Financial and Insurance Activities	Finance
C	Manufacturing	Industrial
B	Mining and Quarrying	Infrastructure
D	Electricity, Gas, Steam and Air Conditioning Supply	Infrastructure
E	Water Supply; Sewerage, Waste Management and Remediation Activities	Infrastructure
F	Construction	Infrastructure
H	Transportation and Storage	Infrastructure
L	Real Estate Activities	Infrastructure
Q	Human Health and Social Work Activities	Life Science
I	Accommodation and Food Service Activities	Services
M	Professional, Scientific and Technical Activities	Services
N	Administrative and Support Service Activities	Services
P	Education	Services
S	Other Service Activities	Services
T	Activities of Households as Employers; Undifferentiated Goods- and Services-producing Activities of Households For Own Use	Services
J	Information and Communication	TMT
R	Arts, Entertainment and Recreation	TMT

C Rapid evidence assessment literature

This sets out the literature sources covered as part of the evidence review:

Zoe Amar and The Skills Platform digital (2020) Charity Digital Skills report (http://report.skillsplatform.org/charity-digital-report-2020/)

DataKind UK and Data Orchard (2017) Data Evolution Project (https://static1.squarespace.com/static/5d514d1775e9c90001345670/t/5d782074524cf43b1782857f/1568153741439/Data+Evolution+Full+Report+Jan2017v2.pdf)

Frontier Economics (2021) Increasing access to data across the economy (https://assets.publishing.service.gov.uk/Government/uploads/system/uploads/attachment_data/file/974532/Frontier-access_to_data_report-26-03-2021.pdf)

Data Orchard (2019) Data Maturity Framework for the Not-For-Profit Sector (https://static1.squarespace.com/static/5d514d1775e9c90001345670/t/5d9f402df0b312eb6c55f69/1570717742668/Data+Orchard+Data+Maturity+Framework+NFP+Sector+2019.pdf)

Department for Digital, Culture, Media & Sport (2017) Unlocking the power of data in the UK economy and improving public confidence in its use (https://www.gov.uk/Government/publications/uk-digital-strategy/7-data-unlocking-the-power-of-data-in-the-uk-economy-and-improving-public-confidence-in-its-use)

Cebr (2016) The Value of Big Data and the Internet of Things to the UK Economy (https://www.sas.com/content/dam/SAS/en_gb/doc/analystreport/cebr-value-of-big-data.pdf)

cloud Thing (2020) 5 ways charities can benefit from better technology (https://www.thirdsector.co.uk/five-ways-charities-benefit-better-technology/article/1701917)

IDC (2020) Market Analysis Perspective: Worldwide Big Data and Analytics Software (https://www.idc.com/getdoc.jsp?containerId=US45534518)

Funraise and Nonprofit Tech for Good (2019) Global NGO technology report (https://assets-global.website-files.com/5da60733afec9db1fb998273/5de8285d137d82cb7d96674e_2019-Tech-Report-English.pdf)

European Commission Expert Group on FAIR data (2018) Turning FAIR into reality (https://ec.europa.eu/info/sites/info/files/turning_fair_into_reality_1.pdf)

People Know How (2016) Big Data and The Third Sector: Opportunities and Challenges (https://peopleknowhow.org/wp-content/uploads/2016/09/bigdata_arthurharvey.pdf)

Lloyds Bank (2020) Transformation with Tech (https://www.lloydsbank.com/assets/resource-centre/pdf/businessdigitalindexreport2020.pdf)

Allied Market Research (2020) Europe Big Data and Business Analytics Market 2020-2027 (https://www.prnewswire.com/news-releases/europe-big-data-and-business-analytics-market-to-reach-105-82-bn-by-2027-at-11-5-cagr-amr-301157758.html)

BGK, BPI-France, British Business Bank, ICO, KFW (2019) (https://www.british-business-bank.co.uk/wp-content/uploads/2019/11/going-digital-the-challenges-facing-european-smes-european-sme-survey-2019_2.pdf)

Kivo, Manifesto and Massive (2019) The Future Charity (https://www.kivotransformation.com/docs/future_charity_report.pdf)

Lloyds Bank and Accenture (2016) UK Business Digital Index (https://www.tpdegrees.com/globalassets/pdfs/research-2016/ukbusinessdigitalindex_oct16.pdf)

Whishworks (2019) The State of Big Data in the UK (https://www.whishworks.com/resource/big-data-report-2019/)

The Royal Society (2019) Dynamics of data science skills (https://royalsociety.org/topics-policy/projects/dynamics-of-data-science/)

Centre for Data Ethics and Innovation (2020) AI Barometer (https://assets.publishing.service.gov.uk/Government/uploads/system/uploads/attachment_data/file/894170/CDEI_AI_Barometer.pdf)

Bennett Institute for Public Policy, ODI, Nuffield Foundation (2020) The Value of Data (https://www.bennettinstitute.cam.ac.uk/media/uploads/files/Value_of_data_summary_report_26_Feb.pdf)

Open Data Institute (2015) A guide to the Open Data Maturity Model (https://theodi.org/article/open-data-maturity-model-2/)

Everis (2016) Study on data sharing between companies in Europe (https://op.europa.eu/en/publication-detail/-/publication/8b8776ff-4834-11e8-be1d-01aa75ed71a1/language-en)

Department for Digital, Culture, Media & Sport (2020) Policy Paper National Data Strategy (https://www.gov.uk/Government/publications/uk-national-data-strategy/national-data-strategy)

Department for Digital, Culture, Media & Sport (2021) Top Ten Tech Priorities (https://dcms.shorthandstories.com/Our-Ten-Tech-Priorities/index.html)

D Supplemental analysis

Note this analysis solely details the results from the research carried out rather than looking to identify confirmed conclusions.

Most important characteristic of data foundations

We asked survey respondents to select the data characteristic that was most important to their success. The was to help identify those data characteristics that could be prioritised from a policy perspective.
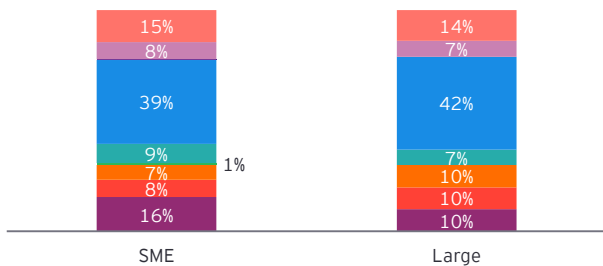
Figure 24 Most important data characteristic
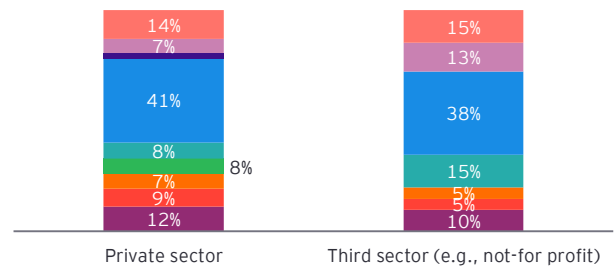
Most important data characteristic
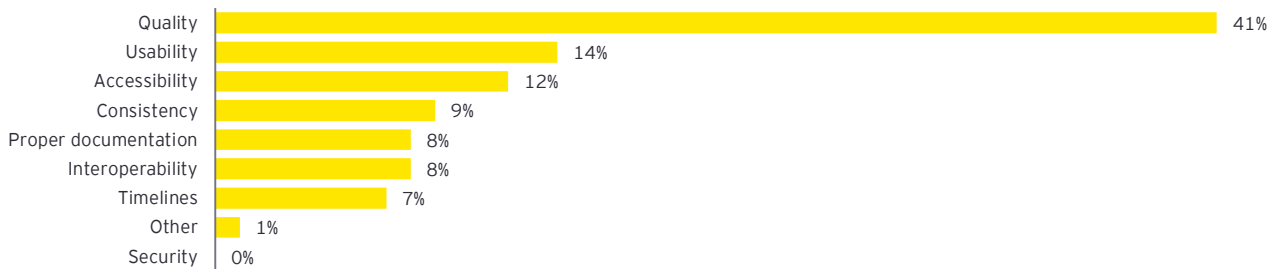
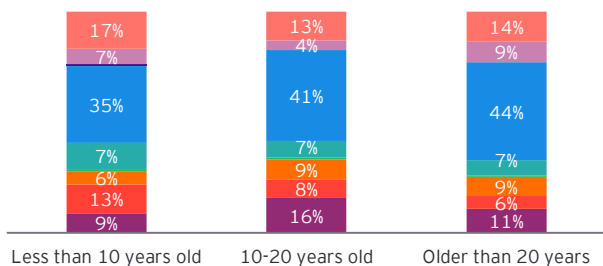|	Accessibility	Consistency	Interoperability	Other	Proper documentation	Quality	Security	Timeliness	Usability
CPR	18%	14%	11%		11%	29%		11%	7%
Finance	20%	12%	8%			40%		8%	12%
Industrial	19%	4%	6%	2%	9%	34%		8%	19%
Infrastructure	6%	15%	6%		12%	39%	2%	5%	15%
Life Science	3%	7%	10%		14%	45%		17%	3%
Services	8%	9%	12%	1%	2%	50%		5%	15%
Third sector	10%	5%	5%		15%	38%		13%	15%
TMT	20%	4%	5%	2%	9%	38%		4%	18%
Total	12%	9%	8%	1%	8%	41%	0%	7%	14%

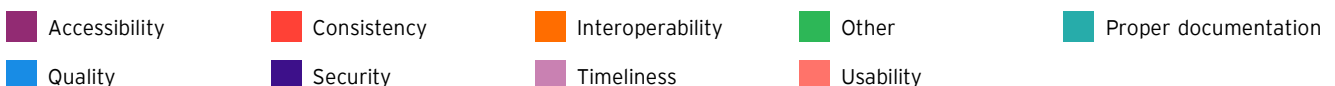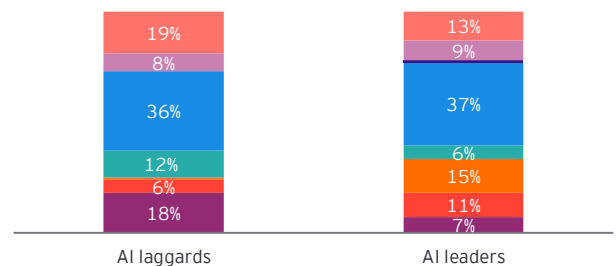**Most important data characteristic by organisation size**

Most important data characteristic by sector

Most important data characteristic by organisation age

Most important data characteristic by AI adoption

Legend: Accessibility, Consistency, Interoperability, Other, Proper documentation, Quality, Security, Timeliness, Usability

Quality is considered the most important data characteristic across key organisational characteristics, including sector, industry, size, age, AI adoption and geographical location

► Quality was identified as the most important data characteristic. This was consistent across all organisation sizes, 42% of Large enterprises and 39% of SMEs selected Quality, as well as across both the private and third sectors, 41% of respondents of the private sector and 38% of the third sector. This finding also was also true across all industry sectors, with 50% of the Services sector identifying Quality as the most important characteristic.

Usability is the second most important characteristic across organisations of different size, sector, industry and age

► The second most important data characteristic was identified in the survey as Usability. This was consistent across key organisation characteristics, including size (15% of respondents from SMEs and 14% of respondents from large organisations), sector (15% third sector and 14% private sector) and age (17% young organisations and 14% old organisations)

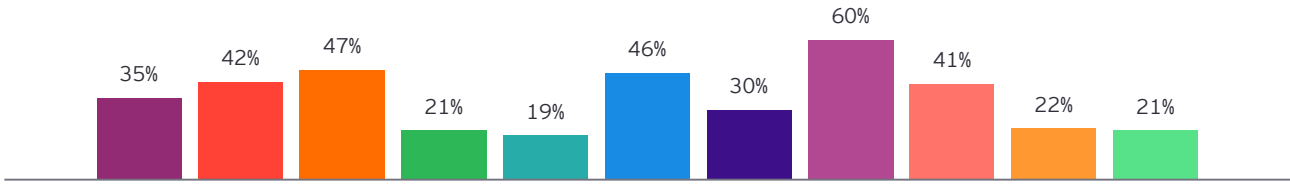**The least frequently identified 'most important' data characteristic was security**

► Security had received a high Perceived Value of Data score of 4.3; however, it was identified as the least frequent 'Most Important' characteristic, selected by only 2% of respondents. This was consistent across all key organisational characteristics. The reason for this difference is that data security is seen as very important, but also as a hygiene factor, rather than a data characteristic that would actively contribute to an organisation's longer terms success.

Interoperability is the second most important characteristic for AI leaders
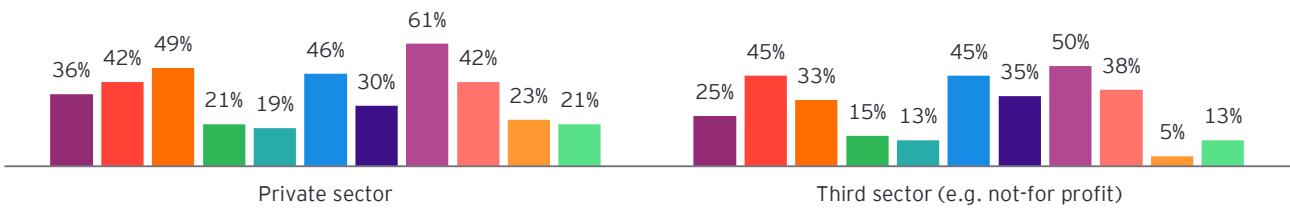
► AI leaders see Interoperability as an important data characteristic compared with AI laggards. 15% of AI leaders said Interoperability is the most important data characteristic compared with just 1% of AI laggards.

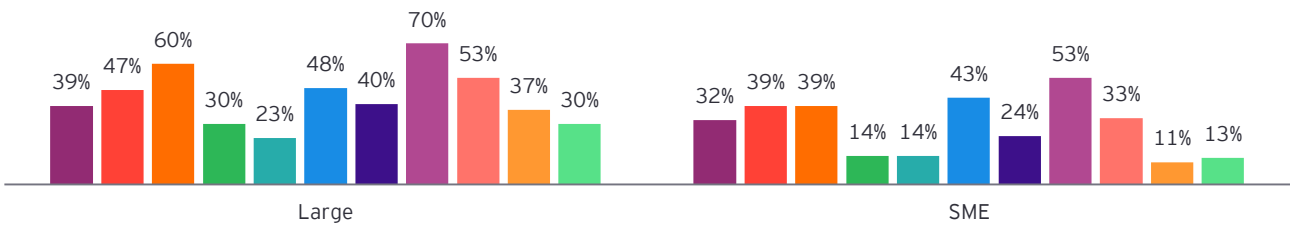## Figure 25 Expected benefits from data strategy and/or data-related initiatives
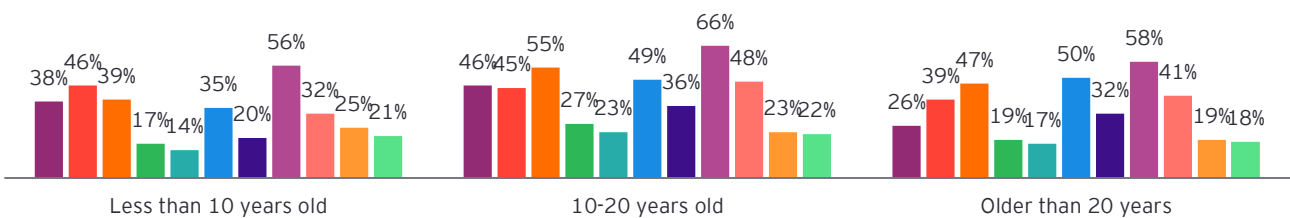
Expected data strategy/initiatives benefits by sector

35% 42% 47% 21% 19% 46% 30% 60% 41% 22% 21%

Expected data strategy/initiatives benefits by sector

Private sector: 36% 42% 49% 21% 19% 46% 30% 61% 42% 23% 21%

Third sector (e.g. not-for profit): 25% 45% 33% 15% 13% 45% 35% 50% 38% 5% 13%

Expected data strategy/initiatives benefits by organisation size

Large: 39% 47% 60% 30% 23% 48% 40% 70% 53% 37% 30%

SME: 32% 39% 39% 14% 14% 43% 24% 53% 33% 11% 13%

Expected data strategy/initiatives benefits by organisation age

Less than 10 years old: 38% 46% 39% 17% 14% 35% 20% 56% 32% 25% 21%

10-20 years old: 46% 45% 55% 27% 23% 49% 36% 66% 48% 23% 22%

Older than 20 years: 26% 39% 47% 19% 17% 46% 32% 58% 41% 19% 18%

Expected data strategy/initiatives benefits by AI adoption

AI leaders: 47% 47% 51% 23% 25% 45% 36% 63% 43% 41% 30%

AI laggards: 30% 41% 46% 21% 16% 46% 28% 59% 41% 15% 17%
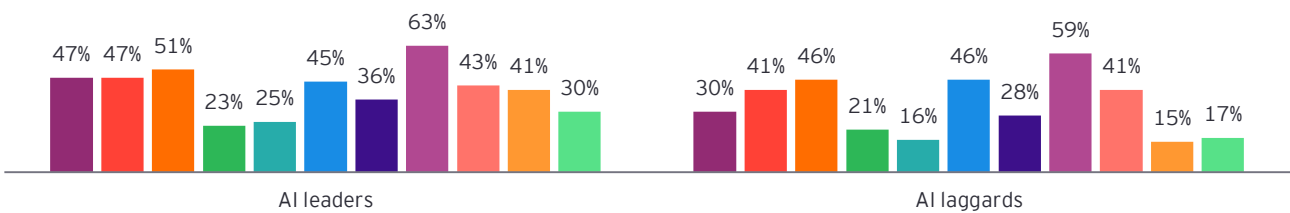
Legend:
- Business / revenue generation - new markets
- Business / revenue generation – new products and services
- Cost reduction
- Greater ability in dealing with market uncertainty and disruptions
- Improved environmental sustainability
- Increased customer engagement
- Increased employee engagement
- Productivity improvement (e.g. operational efficiencies)
- Risk management and compliance
- Support deployment of Artificial Intelligence
- Support deployment of data driven technologies other than Artificial Intelligence Count of ID

Productivity improvement is the leading benefit

▶ Large organisations, SMEs, private and third sector (70%, 53%, 61% and 49% of respondents respectively) mentioned productivity as the key benefits expected to be realised through their data strategy.

Cost reduction was identified as the second largest benefit for AI leaders, large and private sector organisations, whereas it is 'increase in customer engagement' for SMEs, third sector, older organisations and AI laggards

▶ For AI leaders, large organisations and private sector, cost reduction is the second leading benefit with 51%, 60% and 49% of respondents respectively.

▶ For SMEs, third sector, older organisations and AI laggards, increase in customer engagement is the second leading benefit (43%, 44%, 50% and 35% of respondents respectively).

Data strategies and initiatives supporting deployment of AI and other data-driven technologies was a theme more prevalent for AI leaders, large and young organisations and private sector
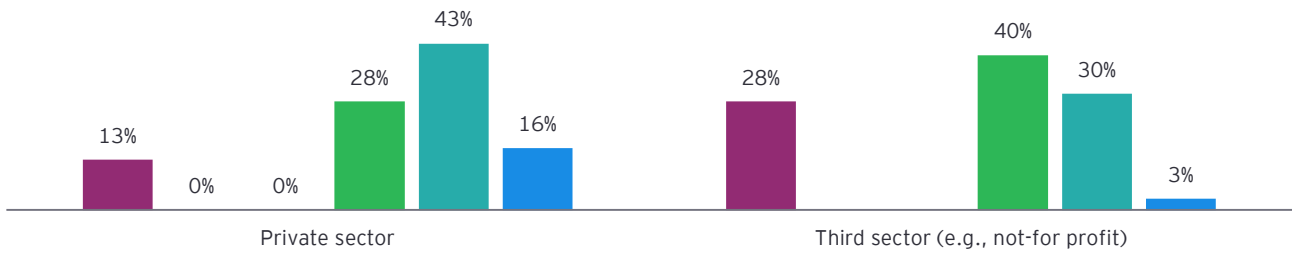
▶ Data strategy supporting deployment of AI and other data-driven technologies was a benefit perceived to be a high priority for private sector (23% said supports AI and 21% mentioned support for other data-driven technologies), whereas for third sector it was low (5% for AI and 13% for other data-driven technologies). Same could be seen for large organisations (37% and 30% respondents mentioned support deployment of AI and other data-driven technologies respectively) compared with SMEs (11% and 13% respondents mentioned support deployment of AI and other data-driven technologies respectively). 41% of AI leaders expect their data strategy and initiatives to support further deployment of AI, whereas 0% of AI laggards expect their data strategy/initiatives to support deployment of AI.
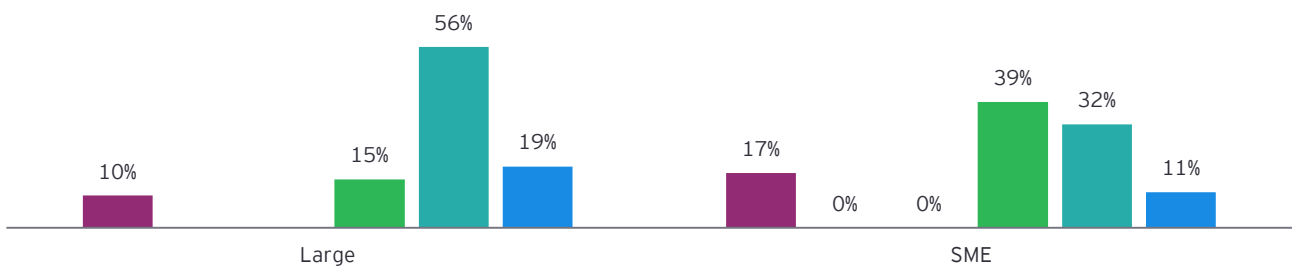
Significant differences between industries

▶ Material differences in expected benefits were identified between industries. This suggests they are industry-dependent.

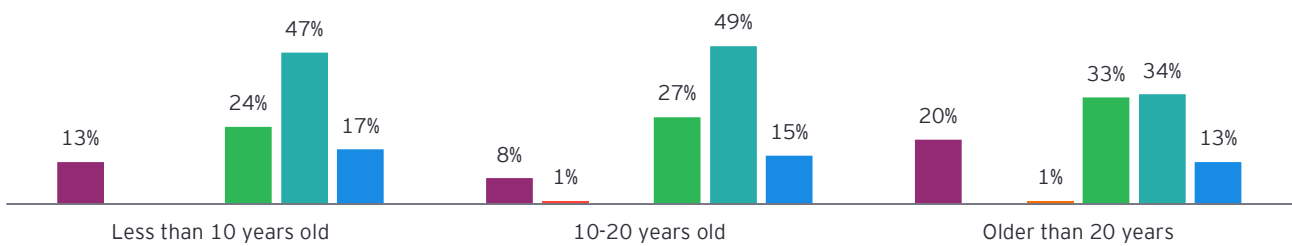## Figure 26   Change in investments in AI over the next three years

Investment plan in AI by sector

Private sector: 13%, 0%, 0%, 28%, 43%, 16%
Third sector (e.g., not-for profit): 28%, 40%, 30%, 3%

Investment plan in AI by organisation size

Large: 10%, 15%, 56%, 19%
SME: 17%, 0%, 0%, 39%, 32%, 11%

Investment plan in AI by organisation age

Less than 10 years old: 13%, 24%, 47%, 17%
10-20 years old: 8%, 1%, 27%, 49%, 15%
Older than 20 years: 20%, 1%, 33%, 34%, 13%

Investment plan in AI by AI adoption

AI laggards: 17%, 0%, 0%, 38%, 37%, 8%
AI leaders: 4%, 7%, 57%, 31%

Legend:
- Don't know
- Significantly decrease
- Decrease
- Keep unchanged
- Increase
- Significant increase
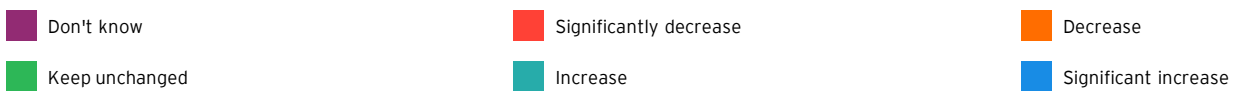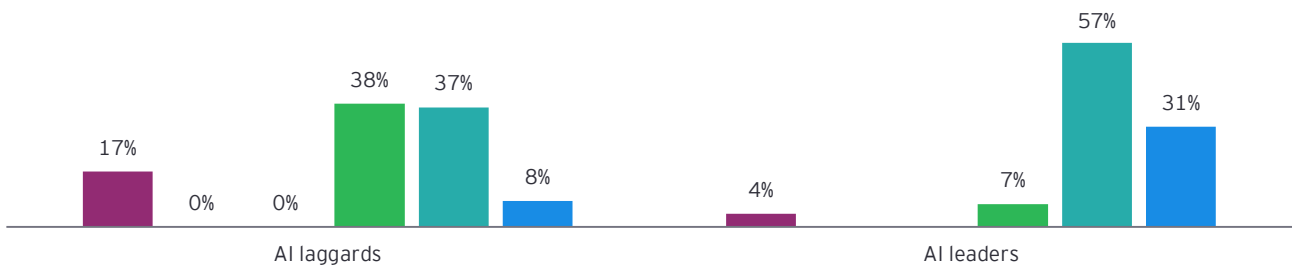
Significant AI investments in private sector and by AI leaders and large organisations

▶ 16% of private sector organisations are planning to significantly increase investments in AI within the next 3 years. Only 3% of third sector organisations plan to significantly increase investments in AI. Almost no organisation is planning to decrease investment in AI.

▶ 88% of AI leaders expect to increase investments in AI (31% significantly) over the next 3 years, in comparison to 45% of AI laggards. 24% of AI laggards also do not know how their investments will change.

▶ 75% of large organisations plan to increase AI investments within the next 3 years. AI investment in SMEs is expected to be relatively less widespread with 43% organisations planning to increase investments.

Increased investments in Finance, Life Science, Services and TMT

▶ 80% of the companies in Finance industry are planning to increase investments, followed by Life Sciences at 65% and Services and TMT at c.60% each.

CPR and Infrastructure characterised by highest number of companies not planning to increase investments

▶ c.40% of companies in CPR and c.36% companies in Infrastructure do not plan to increase investments in AI. Moreover, a small proportion (2%) of Infrastructure companies plan on decreasing the investments.

Figure 27 Change in investments in AI over the next three years by industry
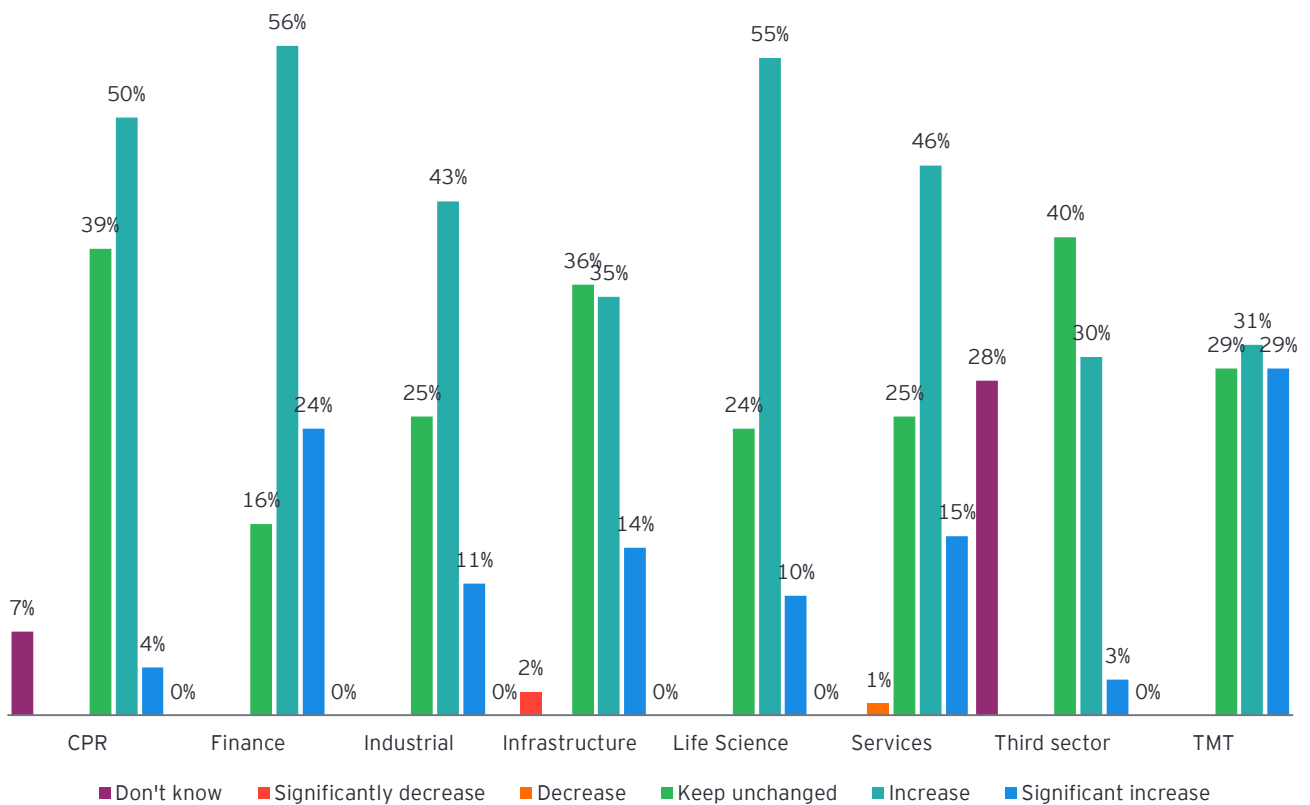
Use and adoption of AI in various business functions

Identifying the business functions that most commonly use AI provides an indication of the prioritised areas and use-cases of AI technology. These functions are driving the AI agenda of the companies, influencing the future direction of the company's efforts in this space.

AI is mostly applied in IT, Technology & Digital, followed by Operations and Logistics, Product Development and Management and Strategy

► Among the organisations surveyed, usage spans across all 12 business functions presented. The distribution of AI usage is primarily concentrated in IT, Techno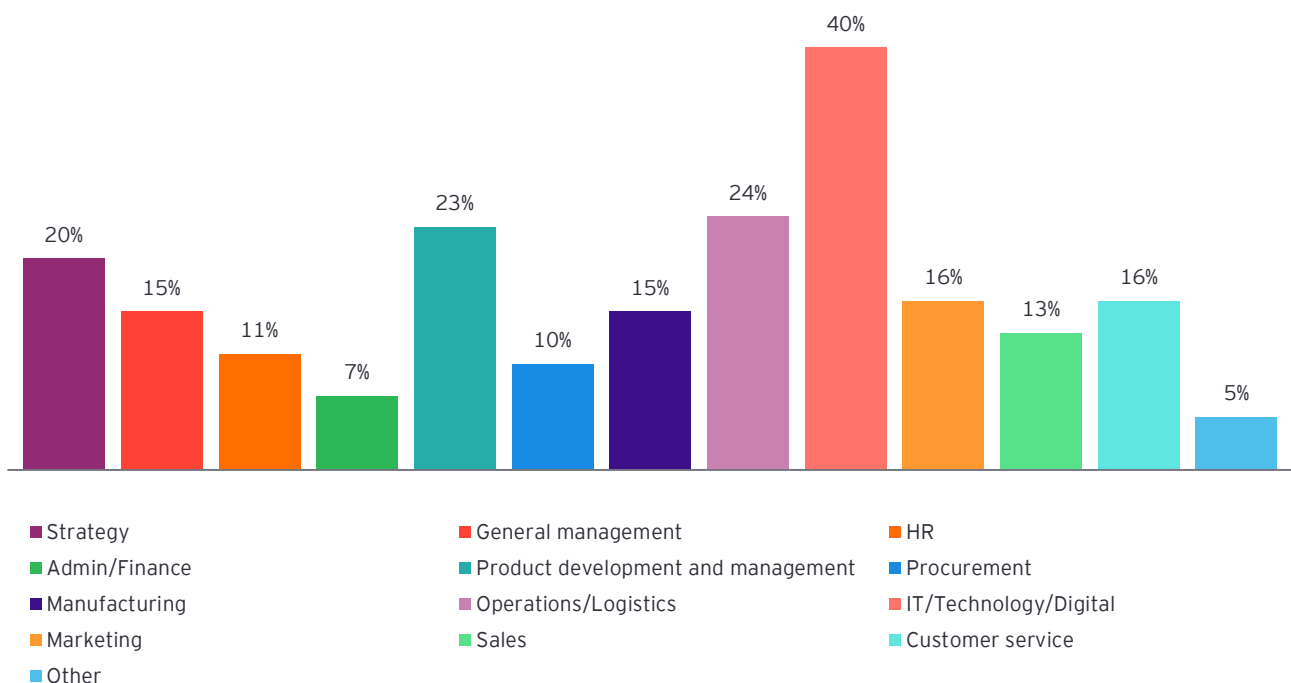logy & Digital (40%), followed by other functions such as Operations and Logistics (24%), Product Development and Management (23%) and Strategy (20%).

► This pattern is similarly reflected in both large organisations and SMEs for the above-mentioned functions. However, use of AI in HR significantly varies among large organisations (19%) and SMEs (6%). This could be explained by the higher number of employees in large organisations, resulting in increased importance of HR as a business function.

Limited use in HR and Procurement

► There are several functions where AI is hardly in used among the participating companies. This includes people-intensive functions such as HR and Procurement.

► This is not due to lack of potentially valuable AI use-cases, which in the case of HR include talent acquisition (avoiding human bias), onboarding (Q&A) or supporting performance evaluation (analysing data).

► Potential hypotheses for this limited use could include prioritising other functions that tangibly impact business performance over these functions, the higher complexity of use-cases in these functions or the sensitive applications of AI in these functions.

Figure 28   Use and adoption of AI across business functions

Strategy ■ **General management** ■ **HR** ■
Admin/Finance ■ **Product development and management** ■ **Procurement** ■
Manufacturing ■ **Operations/Logistics** ■ **IT/Technology/Digital** ■
Marketing ■ **Sales** ■ **Customer service** ■
Other ■

General Management, Administration & Finance and Procurement functions are characterised by more advanced use of AI

► More than 20% of respondents using AI in these functions stated the adoption to be at Advanced stage

Sales is an emerging function characterised by many use-cases of piloting the AI technology

► 13% of the total respondents said AI is used in Sales. Almost half of those respondents (46%) stated that the use-cases are at the piloting stage.

► With a high number of cases at Piloting stage, but the lowest proportion of released cases (19%), Sales appears to be becoming an important function where companies have already started testing the technology and are looking to expand its use.

Figure 29 Use and adoption of AI in business functions

AI adoption in business functions at overall level

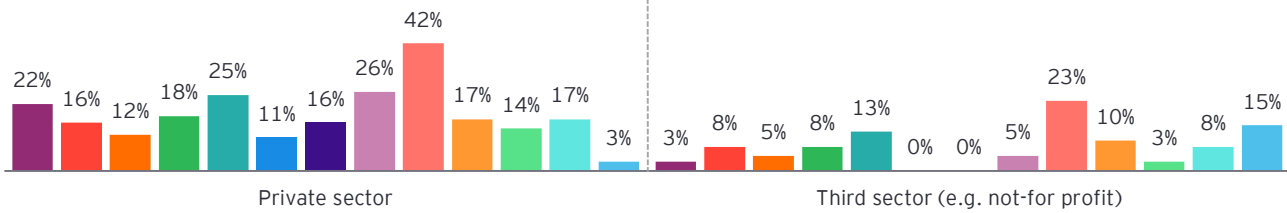| Business function	Advanced	Released	Piloting	Planned
IT/Technology/Digital	16.5%	31.6%	19.0%	32.9%
Operations/Logistics	9.4%	36.5%	24.0%	30.2%
Product development and management	14.1%	32.6%	23.9%	29.3%
Strategy	12.8%	24.4%	24.4%	38.5%
Admin/Finance	21.5%	26.2%	24.6%	27.7%
Customer service	9.4%	29.7%	23.4%	37.5%
Marketing	10.9%	35.9%	20.3%	32.8%
General Management	25.4%	35.6%	18.6%	20.3%
Manufacturing	19.0%	31.0%	22.4%	27.6%
Sales	13.5%	46.2%	21.2%	19.2%
HR	19.0%	11.9%	31.0%	38.1%
Procurement	20.5%	35.9%	17.9%	25.6%
Other		50.0%		50.0%

Use of AI in business function by sector

Use of AI in business function by organisation size
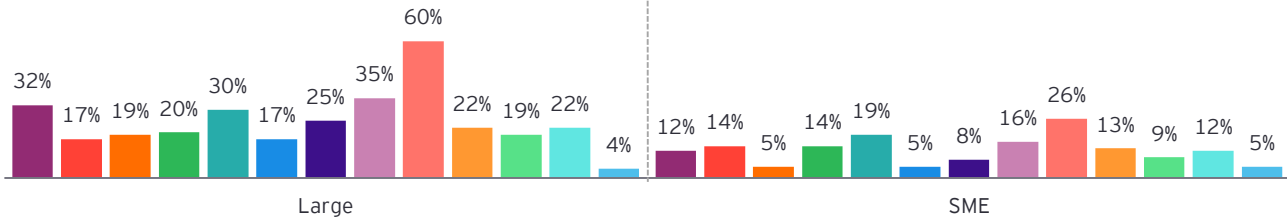
Use of AI in business function by organisation age
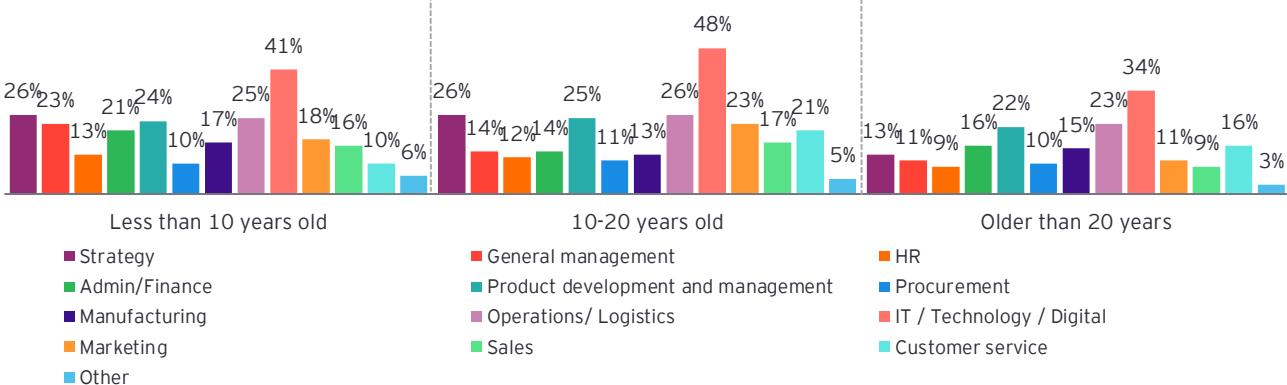
- ► Private sector organisations used AI more frequently across every business function than third sector organisations. Private organisations used AI mainly in IT/Technical/Digital (42%), Operations/logistics (36%) and product development and management (25%) functions. The third sector used AI mainly in IT/Technical/Digital (23%), product development and management (13%) and marketing functions (10%).
- ► Large organisations used AI more frequently across every business function than SMEs. Large organisations used AI mainly in IT/Technical/Digital (60%), Operations/logistics (35%) and strategy (32%) functions. Whereas SMEs used AI primarily in IT/Technical/Digital (26%), product development and management (19%) and marketing functions (16%).
- ► There were no material differences in the use of AI in business functions by organisation age.

AI use cases

We asked participants what AI is currently used for in their organisation:

▶ To predict (i.e., anticipate events and outcomes)

▶ To automate (i.e., handle tasks without human intervention)

▶ To generate insights (i.e., identify and understand patterns and trends)

▶ To personalise (i.e., tailor content and user experience)

▶ To prescribe (i.e., suggest solutions to defined problems)

AI is used for a wide range of applications, mainly for automating, generating insights and predicting

▶ 36% of the respondents stated that AI is used to automate and handle tasks without human intervention, followed by 31% for generating insights to identify and understand patterns and trends, and 30% for predicting or anticipating events and outcomes and generating insights each and 26% for personalisation including creating tailored content and user-experience. 19% of the respondents also highlighted the use case for AI to prescribe or suggest solutions to defined problems.

Automation is the top use case for organisations in the Finance industry

▶ The Finance industry stands out, with 60% of the respondents stating that they use AI for automation. This involves using AI to automate tasks to reduce manual interventions in repetitive tasks and focusing employees' efforts on tasks that cannot be automated.

Using AI to prescribe is particularly common in the Life Sciences industry

▶ 28% of the Life Science respondents stated that their organisation uses AI to prescribe. Life Sciences organisations are using more and more data to be able to diagnose health problems and subsequently suggest potential solutions.

▶ 48% of the companies surveyed in the Finance industry stated that they use AI to personalise content and user experience. This proportion was at 41% in Life Sciences and 36% in CPR. All these industries are characterised by solutions provided at the individual level, such as personalised loans, interest rates in Finance, individual health diagnoses in Life Sciences, and selling products based on buyer profile in CPR, especially in e-commerce.

Figure 30   AI use cases by industry

Reasons AI currently used in organisations at an overall level

■ To prescribe   ■ To predict   ■ To generate insights   ■ To automate   □ To personalise
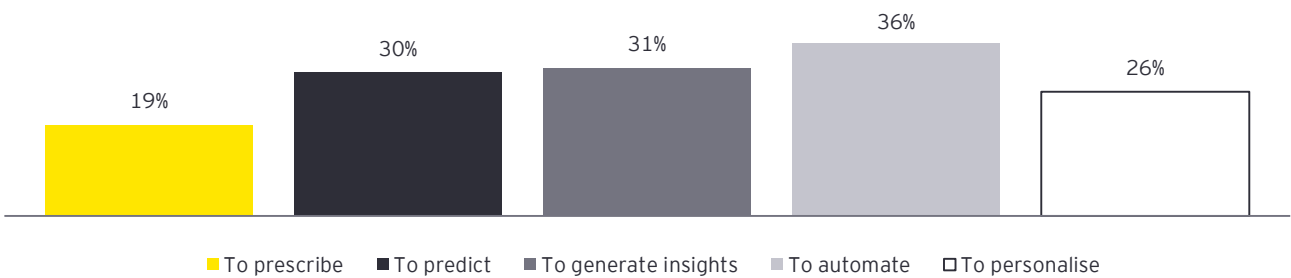
Reasons AI currently used in organisations by industry

■ To prescribe   ■ To predict   ■ To generate insights   ■ To automate   □ To personalise
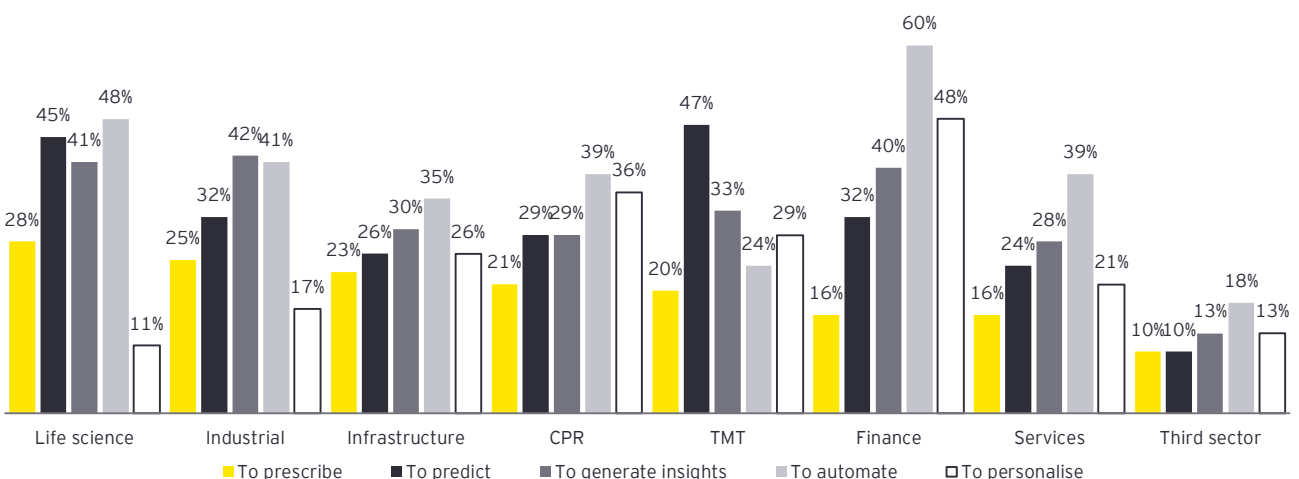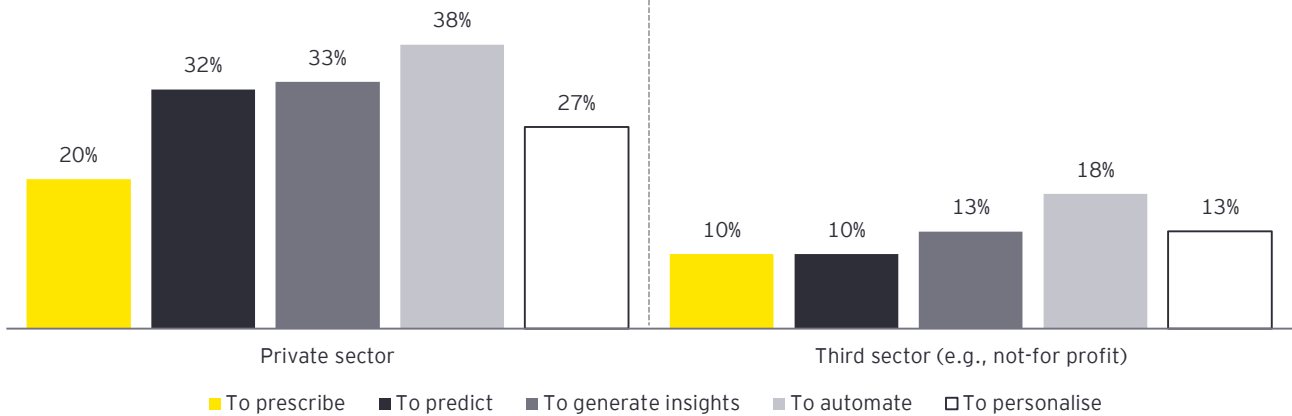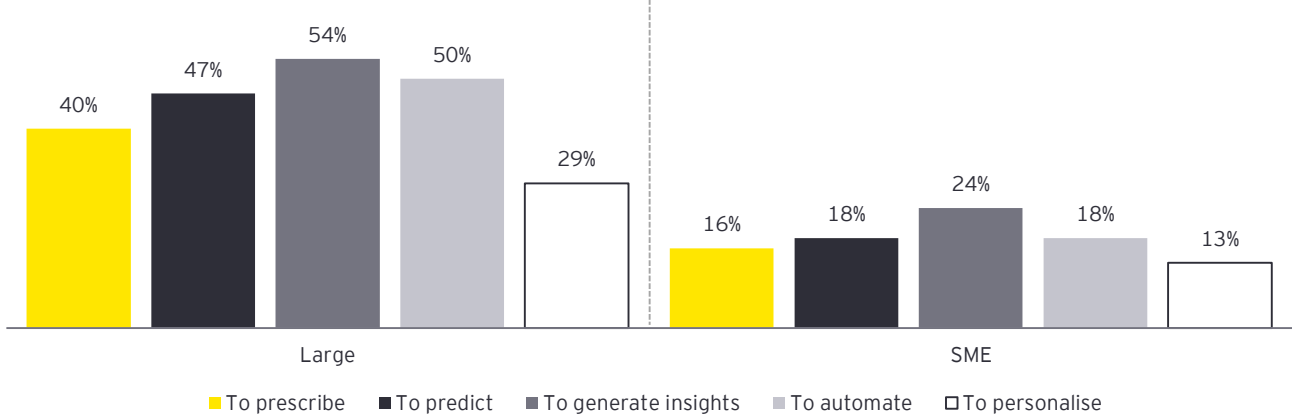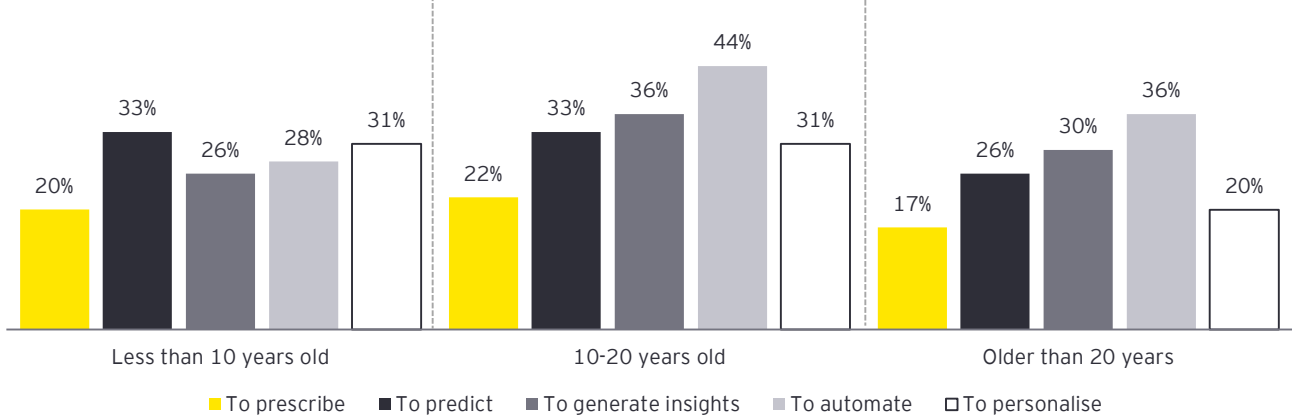
Figure 31 AI use cases by sector, organisation size and age

Reasons AI currently used in organisations by sector

Private sector
- To prescribe: 20%
- To predict: 32%
- To generate insights: 33%
- To automate: 38%
- To personalise: 27%

Third sector (e.g., not-for profit)
- To prescribe: 10%
- To predict: 10%
- To generate insights: 13%
- To automate: 18%
- To personalise: 13%

Legend: ■ To prescribe ■ To predict ■ To generate insights ■ To automate □ To personalise

Reasons AI currently used in organisations by organisation size

Large
- To prescribe: 40%
- To predict: 47%
- To generate insights: 54%
- To automate: 50%
- To personalise: 29%

SME
- To prescribe: 16%
- To predict: 18%
- To generate insights: 24%
- To automate: 18%
- To personalise: 13%

Legend: ■ To prescribe ■ To predict ■ To generate insights ■ To automate □ To personalise

Reasons AI currently used in organisations by organisation age

Less than 10 years old
- To prescribe: 20%
- To predict: 33%
- To generate insights: 26%
- To automate: 28%
- To personalise: 31%

10-20 years old
- To prescribe: 22%
- To predict: 33%
- To generate insights: 36%
- To automate: 44%
- To personalise: 31%

Older than 20 years
- To prescribe: 17%
- To predict: 26%
- To generate insights: 30%
- To automate: 36%
- To personalise: 20%

Legend: ■ To prescribe ■ To predict ■ To generate insights ■ To automate □ To personalise

► Private sector organisations had more use cases for AI than third sector organisations. For both the private and third sectors, the main AI use case was automation (38% and 18%, respectively) and the least common use case was prescription (20% and 10%, respectively).

► Large organisations had more use cases for AI than SMEs. For both large organisations and SMEs, the main AI use case was automation (54% and 24%, respectively) and the least common use case was prescription (29% and 13%, respectively).

► Younger organisations (less than 10 years old) used AI more frequently to personalise than older organisations (31% and 20% respectively).

Figure 32   Top three challenges in adopting and improving data foundations by key organisational characteristics

Current		Category		Future
Lack of funding	23%	**Third sector**	25%	Lack of funding
Lack of management engagement	17%		19%	Lack of skilled personnel
Technology landscape	14%		14%	Cultural barriers
Existing infrastructure	15%	**Private sector**	13%	Market uncertainty
Lack of skilled personnel	15%		11%	Lack of skilled personnel
Lack of funding	10%		11%	Existing infrastructure
Lack of skilled personnel	15%	**SMEs**	14%	Lack of skilled personnel
Lack of funding	13%		13%	Lack of funding
Existing infrastructure	12%		12%	Market uncertainty
Existing infrastructure	17%	**Large**	13%	Existing infrastructure
Lack of skilled personnel	13%		13%	Market uncertainty
Cultural barriers	12%		12%	Technology landscape
Lack of skilled personnel	16%	**Young organisations (less than 10 years old)**	18%	Market uncertainty
Market uncertainty	15%		15%	Lack of skilled personnel
Existing infrastructure	14%		12%	Lack of compelling business case
Lack of skilled personnel	15%	**Old organisations (older than 20 years)**	13%	Lack of funding
Existing infrastructure	15%		13%	Existing infrastructure
Lack of funding	13%		12%	Lack of skilled personnel
Technology landscape	16%	**AI leaders**	18%	Lack of skilled personnel
Lack of skilled personnel	13%		12%	Market uncertainty
Existing infrastructure	12%		11%	Risk/disruption to the organisation
Lack of funding	16%	**AI laggards**	16%	Lack of compelling business case
Market uncertainty	15%		16%	Lack of funding
Lack of compelling business case	13%		14%	Market uncertainty

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