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What factors influence perceived artificial intelligence adoption by public managers?

A survey among public managers in seven EU countries

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Contents

Abstract

The adoption of artificial intelligence (AI) in the public sector is now reaching a stage where, drawing on the experience of early pilots and adoptions, EU public administrations are starting to face the challenges of implementing AI solutions. In response, this study investigates AI adoption in the public sector with a twofold goal:

- Add evidence to the existing body of knowledge to have a better understanding of the dynamics underlying AI adoption in the EU. We do this by providing quantitative (survey) insights into AI readiness and adoption in the public sector, across different country contexts. By offering a picture of the status of AI adoption and readiness in public administrations, we identify the main challenges and drivers of AI adoption, which are required for ensuring AI's trustworthy use.
- Define recommendations for managers in the public sector and public administrations. Based on the insights from the first aim, we formulate ways forward to inform policymakers.

We surveyed 576 public managers in seven countries: Germany, Spain, France, the Netherlands, Austria, Poland and Sweden. The sample was diverse in age, job level, organisation size and geographical origin. We asked each of them about the level of AI adoption in their organisation. This was measured in two ways: we asked specifically about the extent to which they thought that their organisation had implemented AI projects in service delivery, internal operations and policy decision-making. Next, we asked about the exact number of projects that were either planned or implemented, with the response options of 0, 1, 2–5 or more than 5.

Building on the latest scientific insights, we look at what combination of technological, organisational, environmental and individual-level factors contributes to AI adoption.

Based on our research, we have three key conclusions:

1. AI adoption is no longer a promise; it is a reality, in particular for service delivery and internal operations.
2. Soft factors and in-house expertise are important internal factors for AI adoption.
3. Citizen needs are an important external factor for AI adoption.

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Executive summary

Policy context

The adoption of artificial intelligence (AI) in the public sector is now reaching a stage where, drawing on the experience of early pilots and adoptions, EU public administrations are starting to face the challenges of implementing AI solutions. The Joint Research Centre (JRC) monitors developments by carrying out in-depth case studies and sets out guidelines for AI adoption in the public sector.

This research aims to investigate the adoption and use of AI in public administrations by looking at the different elements that should coexist within the public sector to foster the adoption of AI solutions. In particular, the research will address several prerequisites for sustainable and trustworthy adoption in EU Member States.

Key conclusions

Based on our research, we have three key conclusions.

1. AI adoption is no longer a promise; it is a reality, in particular in service delivery and internal operations.

The first conclusion is that most public managers report that their organisations either are planning one or more AI initiatives (63.1%) or have already implemented them (51.8%). On the other hand, around 15% of public managers in our sample do not know the number of planned/implemented projects, 34% have not (yet) implemented AI and 21% have not reached the stage of planning an AI project. Overall, this means that AI in the public sector is no longer a promise but is becoming a reality. More specifically, AI is planned/implemented in service delivery and internal operations, but not to the same extent in policy decision-making.

2. Soft factors and in-house expertise are important internal factors for AI adoption.

We analysed the factors associated with AI adoption and found that the perceived benefits of AI are positively related to the perceived adoption of AI. Other factors include what has been called 'organisational software', which comprises softer factors, such as leadership and an innovative culture. In addition, a clear AI strategy and in-house expertise are needed. With regard to the latter, it should be noted that expertise is required not only on the technical aspects of AI but also on its legal, ethical and governance aspects. This means there is no quick fix when it comes to increasing AI adoption; it is likely that long-term investment in leadership, culture and strategic alignment will be required.

3. Anticipated citizen needs are an important external factor for AI adoption.

In addition to taking into account these organisational factors, public managers look at citizens and try to anticipate their needs for AI solutions. The more strongly public managers believe citizens want AI-powered services, the greater the adoption of AI solutions. This underscores the pivotal importance of citizens in the adoption of AI technology. Surprisingly, other external stakeholders matter less for AI adoption: national government support, competition with other, similar, organisations and collaborations with private companies have less marked effects.

Methods

This study had the following research design.

- We surveyed 576 public managers in seven countries: Germany, Spain, France, the Netherlands, Austria, Poland and Sweden. Because of the broad scope of the survey, we cannot say the sample is representative, but it was diverse in terms of age, job level, organisation size and geographical origin.
- We asked them about the levels of AI adoption in their organisations, specifically about AI projects in service delivery, internal operations and policy decision-making.
- Building on the latest scientific insights, we looked at what combination of technological, organisational, environmental and individual-level factors contributes to AI adoption.

Main findings

1. In all surveyed countries, the majority of public managers (52%, or 300 managers) indicated that they had at least one AI project fully adopted and in use in their organisations.
2. We found that most adopted AI systems are used for service delivery and internal operations. Fewer AI systems are related to policy decision-making.
3. Six factors have a significant contribution to AI adoption: the anticipated benefits of AI for the organisation, in-house expertise, strong AI strategy, a culture open to innovation, leadership support and the anticipated needs of citizens for AI solutions in government.

Policy recommendations

Based on these conclusions, we have the following policy recommendations.

1. Pay attention to AI and digitalisation in leadership programmes, organisational development and strategy building.
2. Broaden in-house expertise on AI. This should include not only technical expertise but also expertise on ethics, governance, management, etc. To keep such expertise in house, it should ideally be acquired through training or the recruitment of new talent, instead of by engaging with external experts.
3. Monitor citizen needs for digital improvements in government service delivery. Demand from citizens is an important aspect of public organisations' external environment, and plays a role in their adoption of AI. Therefore, citizen needs should be monitored and investigated more closely.

Related and future Joint Research Centre work

The research was developed, managed and overseen by the JRC's Innpulse team, which focuses on the innovation of public services and the digital transformation of governance. The findings of the research have been incorporated into the scope of Public Sector Tech Watch, a specialised observatory that tracks, evaluates and shares information on the adoption of emerging technologies in the public sector across Europe. This observatory is under the joint administration of the Directorate-General for Digital Services and the JRC, the latter serving as its scientific partner. The JRC is deeply invested in aiding public authorities to embrace AI by providing scientific insights and policy guidance. This dedication is set to persist, with plans to conduct additional research in this area in the future.

Quick guide

The first section sets the stage for the study and poses the research question. Section 2 delves into the policy background, examining pertinent regulatory measures and policy efforts within the EU. Section 3 analyses and reviews prior research on the subject. Section 4 outlines the methodology employed in the investigation, detailing how data were gathered and analysed. Section 5 shares the results derived from the study. The final section wraps up with recommendations for policy implementation based on the study's conclusions.

1 Introduction

The EU aims to become a global leader in trustworthy artificial intelligence (AI) and wants to accelerate AI investments among EU Member States. The adoption of AI in the public sector is now reaching a new stage where, drawing on the experience of early pilots and adoptions, EU public administrations are starting to face the challenges of implementing AI solutions that are to be sustainably embedded in each agency's organisational processes, principles and skillsets (Jorge Ricart et al., 2022). The Joint Research Centre (JRC) monitors developments by carrying out in-depth case studies (Tangi et al., 2023) and sets out guidelines for AI adoption in the public sector (Manzoni et al., 2022). In particular, the research will address several prerequisites for sustainable and trustworthy AI adoption in EU countries.

The study has a twofold goal.

- Add evidence to the existing body of knowledge to have a better understanding of the dynamics underlying AI adoption in the EU. We do this by providing quantitative (survey) insights into AI readiness and adoption in the public sector, across different country contexts. By offering a picture of the status of AI adoption and readiness in public administrations, we identify the main challenges and drivers of AI adoption and an approach for ensuring AI's trustworthy use.
- Define recommendations for managers in the public sector and public administrations. Based on the insights from the first aim, we formulate ways forward to inform policymakers.

The research aims to investigate the adoption and use of AI in public administrations by looking at the different elements that should coexist within a public administration to ensure the trustworthy use of AI solutions. The adoption of AI in public administration demands a thorough understanding of relevant AI readiness factors, as AI is complex to implement due to its technical characteristics and to knowledge barriers (Jöhnk et al., 2021). Research on AI readiness and adoption is only in its infancy (Jöhnk et al., 2021).

AI adoption and readiness have previously been discussed using different frameworks in the literature. One of the predominant theoretical frameworks is the technology–organisation–environment (TOE) framework. Generally, the TOE framework brings together technological, organisational and environmental factors to investigate firms' adoption and implementation of technological innovations. The framework has been synthesised previously and applied to technology in other settings (Aboelmaged, 2014; Dewi, 2018). Overall, the literature stresses that it is important to recognise that the adoption of AI within public organisations is driven not only by technological (push) factors but also by organisational factors, such as culture, and by external factors, such as citizen demands and institutional arrangements (Alsheibani et al., 2018; Madan and Ashok, 2023; van Noordt and Tangi, 2023).

Based on this assumption, we developed a theoretical model that identifies technological, organisational and environmental (institutional) factors that influence AI readiness. We assume that they will positively influence AI adoption. In addition, we enhance the TOE framework by incorporating a factor at the individual level: the personal perceptions of AI usage held by public managers.

In addition, we further specify the environmental factors that affect AI adoption in the public sector.

This leads to the following central research question: **What technical, organisational, environmental and individual-level factors affect AI adoption in public sector organisations?**

We answer this question by surveying 576 public managers in seven countries: Germany, Spain, France, the Netherlands, Austria, Poland and Sweden. This is one of the first surveys to get a comprehensive cross-national picture of AI adoption determinants.

2 Policy context

The EU's active engagement in AI policy began with the 2018 declaration of cooperation on AI, which saw Member States committed to jointly fostering advancements in AI while addressing its broad implications. The 2020 revision of the coordinated plan on AI marked a significant advancement, pinpointing AI's role in the public sector as a vital area for the EU's strategic leadership.

Presently, numerous initiatives and legislative measures are under way to facilitate AI integration into public administration. This chapter encapsulates the legislative landscape and principal initiatives associated with this report's objectives. For an exhaustive examination, readers can refer to a study published in 2024 (European Commission, 2024).

2.1 Legislative framework

In recent years, the European Commission has established a comprehensive legislative package aimed at regulating the use of new technologies, including AI. Although these regulations are not tailored specifically towards the public sector, they have substantial implications for it. The most critical regulations in this context include the AI Act and the Interoperable Europe Act.

The AI Act, proposed in 2021 and entered into force on 1 August 2024, establishes a risk-based approach to regulating AI applications. It bans systems posing unacceptable risks and delineates high-risk applications that will be subject to stringent controls. Further, the act encourages innovation through regulatory experimentation areas and the formation of both the European AI Board and an EU database for high-risk AI systems.

The Interoperable Europe Act, put forward in 2022 and entered into force on 11 April 2024, aims to enhance the cross-border interoperability of IT systems employed in public services. It introduces the Interoperable European Board, responsible for curating a shared strategic agenda for cross-border interoperability, and mandates interoperability assessments for IT systems that operate and exchange data across borders. In addition, it announces the launch of the Interoperable Europe portal, a collaborative platform for sharing and reusing IT solutions. The act also endorses innovation by way of regulatory experimentation areas and government technology (govtech) partnerships.

Relevant EU policy frameworks include, among others:

- the Digital Markets Act, designed to establish equitable conditions within the digital marketplace by overseeing large online platforms and fostering competition, innovation and consumer choice,
- the Digital Services Act, intended to set definitive regulations for digital service providers, thereby ensuring user safety online and enhancing transparency and accountability,
- the Cybersecurity Act, dedicated to augmenting the EU's cybersecurity capabilities, encouraging Member State collaboration and guaranteeing a high level of cybersecurity throughout the EU,
- the Data Act, designed to prescribe unified guidelines on data accessibility for business-to-consumer, business-to-business and public–private exchanges,
- the Data Governance Act, intended to increase trust in data sharing, strengthen mechanisms to increase data availability and overcome technical obstacles to the reuse of data.

2.2 Public Sector Tech Watch: a European platform for artificial intelligence and advanced technologies

A noteworthy initiative is Public Sector Tech Watch (PSTW)[1], which supports this current study. Established in September 2023 and managed by the European Commission's Directorate-General for Digital Services and the JRC, PSTW operates on the Interoperable Europe Portal. It provides a comprehensive resource for public sector employees, policy strategists, private enterprises, and academics and research bodies.

As a knowledge centre, PSTW facilitates the sharing of insights, experiences and educational resources among its members. It bolsters the European Commission's endeavours to promote digital transformation and system compatibility within the European public sector. The establishment of PSTW seeks to bridge the knowledge gap regarding the advantages of novel technologies in public administration and to aid in devising effective strategies through collective expertise and experiences.

It contains many useful resources, including a large database of more than 1 600 use cases of AI and other emerging technologies in the public sector. It also aims to foster a collaborative environment where public administrations can share their practices and experiences. For example, it has launched a Best Cases Award, for which public administrations can submit their use cases to foster an organic learning process among Member States.

Furthermore, PSTW's mission includes generating knowledge to aid public administrations in their pursuit of innovation. This report is a component of its extensive research conducted on public sector AI adoption.

1. https://joinup.ec.europa.eu/collection/public-sector-tech-watch

2.3 Additional EU initiatives on artificial intelligence in public administration

Other significant EU initiatives related to AI in the public sector are worth mentioning, such as the Technical Support Instrument (TSI) projects, particularly the flagship project on AI-ready public administration. This initiative is part of the TSI programme, offering custom technical expertise to Member States and assisting them in AI adoption preparedness; this encompasses enhancing computing and data infrastructure, interoperability, IT and data governance, digital skill development and regulatory mapping in light of impending EU digital legislation, including the AI Act.

In October 2024, the European Commission adopted a communication on enhancing the European administrative space, which includes actions aimed at supervising AI technologies and increasing public administrations' readiness to integrate AI technologies into their operations in a safe and trustworthy way.

The AI procurement community aids public procurers in acquiring AI solutions that are trustworthy, fair and secure. A key endeavour of this community involves creating model EU AI contractual clauses for pilot usage in AI system procurements.

Govtech Connect and Govtech4all aim to nurture the European govtech ecosystem. Govtech Connect includes various initiatives that bring together the govtech innovation community, while Govtech4all focuses on initial implementation through three pilot projects.

3 What drives artificial intelligence adoption in the public sector?

AI has emerged as a transformative technology with profound implications for the public sector (Margetts and Dorobantu, 2019; Tangi et al., 2022). Its potential to automate tasks, enhance decision-making processes and optimise resource allocation has garnered significant attention from governments and public organisations worldwide. By harnessing the power of AI, governments can address myriad issues, such as streamlining administrative processes or strengthening citizen engagement (Moon, 2023). At the same time, there are worries about the speed of development and whether governments can keep control of AI. Scholars have argued that renewed institutional (Grimmelikhuijsen and Meijer, 2022) and accountability (Busuioc, 2021) arrangements are needed to ensure the trustworthy use of AI in the public sector.

AI may be one of the most important developments for public organisations; therefore, we need to understand the factors that drive, or hinder, AI adoption. Adoption is defined as a decision to make full use of technology, and encompasses the stages of integration, implementation and use (Rogers, 2010). AI adoption refers to the process by which organisations and institutions integrate, implement and use AI technologies in their operations, strategies and decision-making frameworks. Several frameworks have been proposed to explain the adoption of AI and other emerging technologies (see, for example, Maragno et al., 2023; Mikalef et al., 2022).

Drawing from existing scientific research on the subject, our investigation encompasses a diverse array of factors related to technology, organisation and the broader environment. These factors have been classified according to the TOE framework, supplemented by insights from a few previous studies that applied this framework in comparable contexts (see, for example, Maragno et al., 2023; Mikalef et al., 2022; Neumann et al., 2022).

A particularly crucial area of analysis concerns environmental factors. To date, most research has concentrated on AI adoption in the private sector (see, for example, Alsheibani et al., 2018; Hradecky et al., 2022), often overlooking distinctive elements of the public sector environment. This gap necessitated the tailoring of existing factors to align with the specificities of the public sector. For example, our research examines the impact of perceived pressure from citizens in either promoting or inhibiting AI adoption, along with legal and political influences (Grimmelikhuijsen and Feeney, 2017; Meijer, 2015; Selten and Klievink, 2024; van Noordt and Tangi, 2023). So far, only a few studies have explicitly acknowledged these unique environmental factors (Grimmelikhuijsen and Meijer, 2022; Madan and Ashok, 2023; Mikalef et al., 2022).

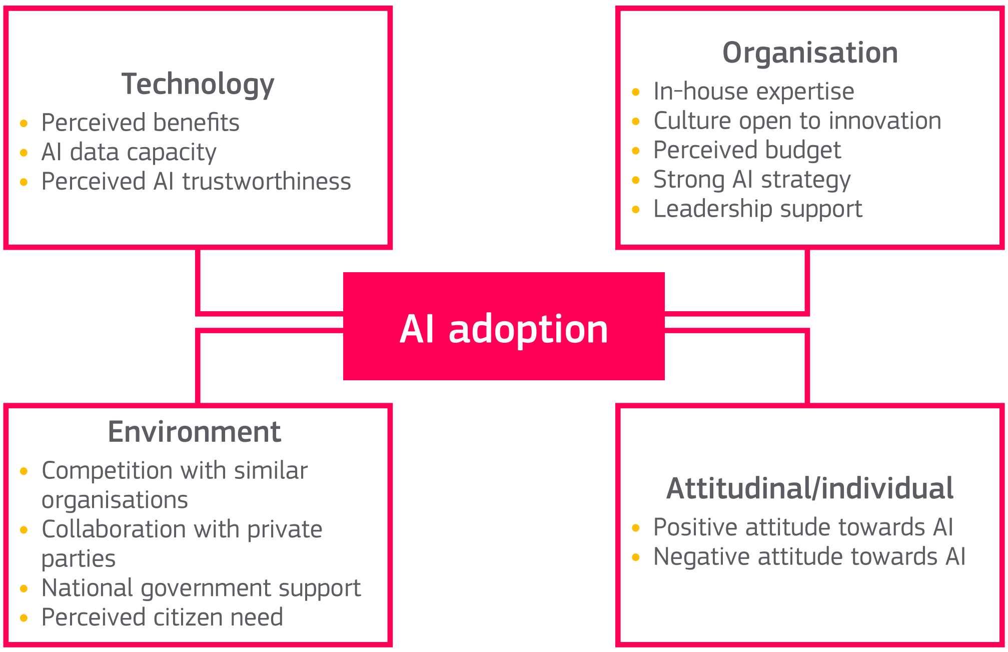
In addition, we have expanded the TOE framework to incorporate individual-level factors. Previous theoretical models for exploring AI adoption in the public sector, including the TOE framework, have largely disregarded the significance of individual-level influences. Typically, the TOE framework has focused on broader macro- and meso-level determinants, such as the legal environment or policy strategies that support AI adoption, leading to somewhat incomplete explanations for AI adoption in the public sector. Therefore, in our study, we introduce the individual perceptions of public managers regarding AI as a factor potentially influencing adoption.

The review of the literature led us to develop the framework depicted in Figure 1. This framework identifies a set of factors, based on the extant literature in the field, that are believed to affect AI adoption. These encompass the perceived benefits and trustworthiness of new technology; organisational culture and leadership; and perceived pressure from citizens. To the best of our knowledge, the significance of these factors for AI adoption has not previously been evaluated through quantitative analysis.

For the purpose of the study, we derived variables from each factor to quantitatively measure their its impact on AI adoption.

Figure 1

Overview of possible factors influencing AI adoption.



Source: *JRC own elaboration.*

4 Methods in brief

4.1 Data collection

Here we provide a brief overview of the survey method.

We carried out a cross-national survey for this report. The survey design allows users to collect data on many variables and a large number of subjects. Data were collected using Dynata between 1 March 2024 and 1 April 2024. Dynata is a large, worldwide platform for data collection. It randomly draws participants from a variety of panels with survey respondents, including more traditional research panels where respondents regularly participate in research, and also panels with participants that have indicated their willingness to participate in research on a one-time basis.

Since the goal of this research is to add evidence on adoption factors in the public sector, we asked Dynata to target participants with a management function working in local or national governments (i.e. **public managers**). In addition, we included a filter question asking respondents whether they worked for the government, another public sector organisation or the private sector. The last category of respondents was not allowed to continue to the survey and was rerouted to an exit page. We will describe the sample selection and composition in the next section.

We selected seven countries for participation in this study: Germany, Spain, France, the Netherlands, Austria, Poland and Sweden. Altogether these countries are a mixture of larger and smaller Member States and spread across all geographical regions of the EU.

Because of the specificity of the sample (public managers), Dynata could provide a maximum of 60 respondents from smaller countries and around 100 respondents from larger countries. In total Dynata collected 576 responses.

We first developed an English-language master version of the survey. Next, the survey was translated by the professional translation bureau of the European Commission into the local languages of the selected countries (Dutch, French, German, Polish, Spanish, Swedish). Finally, the translated versions were checked by researchers with native proficiency in that language to point out any errors or awkwardness in these translated surveys.

The responses have been analysed in the context of the current report. Moreover, the dataset with the entire sample has been published as open data in the JRC data catalogue.

4.2 Survey design

The main dependent variable (DV) in this study was AI adoption as perceived by generic public managers. These managers may not have a complete view of the actual AI adoption in their organisations, leading to measurement errors in our DV. Therefore, we specified the DV to measure adoption in an organisational unit the managers knew best. Specifically, at the start of the survey each respondent was prompted with the following message: ‘Where the questions say “organisation”, you can also think about your team or department when answering the questions if you feel more confident doing so.’

To measure **perceived adoption**, we asked managers if their organisation had adopted AI in three relevant domains: (1) service delivery, (2) internal operations and (3) policy decision-making. Answer categories were on a 7-point Likert scale: 1 – Strongly disagree, 2 – Disagree, 3 – Somewhat disagree, 4 – Neither disagree nor agree, 5 – Somewhat agree, 6 – Agree, 7 – Strongly agree (Cronbach’s alpha: 0.84).

The independent variables were crafted based on a review of the current literature and by adapting the TOE framework with the addition of the individual-level factor, as outlined in the previous section and illustrated in Figure 1. Each variable – here, ‘variable’ refers to a specific element within the TOE categorisation, such as ‘perceived benefits’ – was represented by a minimum of three questions designed to describe it. Respondents were required to respond to each question using a Likert scale ranging from 1 to 7, indicating their level of agreement with the statement. The full questionnaire can be found in the Appendix.

4.3 Data analysis

Data analysis was conducted using two distinct and complementary approaches.

The initial approach involved calculating and examining basic statistics for each question. Specifically, for questions using a Likert scale, the average score for each question was determined to explore the general level of agreement. In addition, the percentage distribution of responses for each option was calculated. These fundamental statistics are valuable for understanding the collective stance of managers regarding each factor.

The second approach was to carry out a regression analysis of the complete dataset to ascertain which variables significantly impact AI adoption. This analysis represents the cornerstone of the entire report, as it seeks to identify the factors that are instrumental for AI adoption in the public sector. The insights drawn from this analysis form the groundwork for the report’s conclusions and subsequent policy recommendations.

The next section presents the findings from this analysis. For the purposes of this report, only the factors that were deemed significant based on the regression analysis are examined and detailed.

5 Results

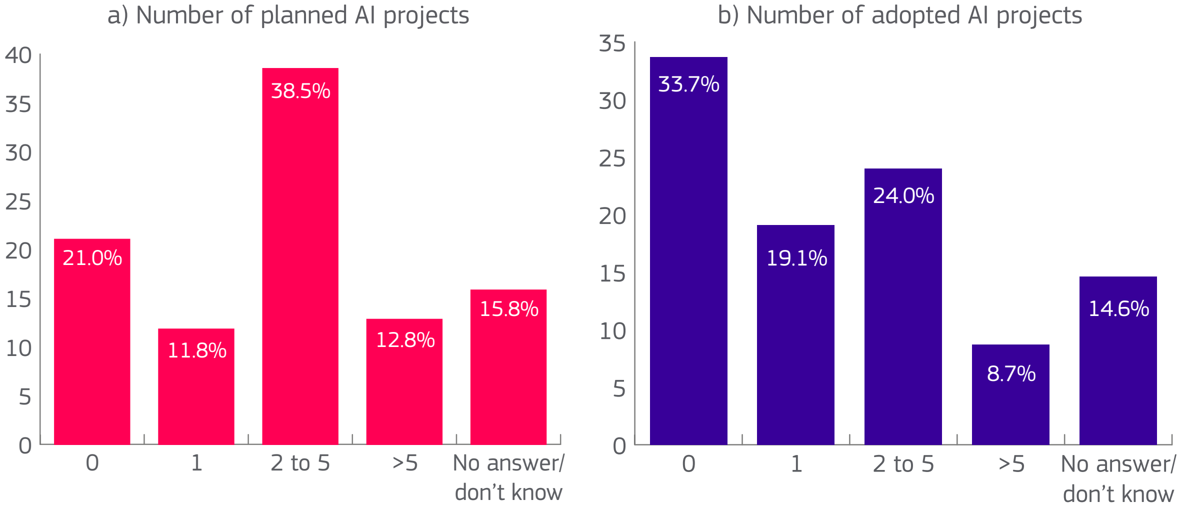
The results are presented in two parts. Initially, we report on the DV (i.e. AI adoption). Following that, the section proceeds with the outcomes of the regression analysis and the basic statistics on the significant independent variables.

5.1 State of artificial intelligence adoption

The bar charts in Figure 2 show the numbers of planned and adopted AI projects across our sample. While this sample cannot be considered to perfectly represent the views of all public managers in the countries we surveyed, the responses do give an impression of the current state of AI adoption.

Figure 2

Adopted AI projects.



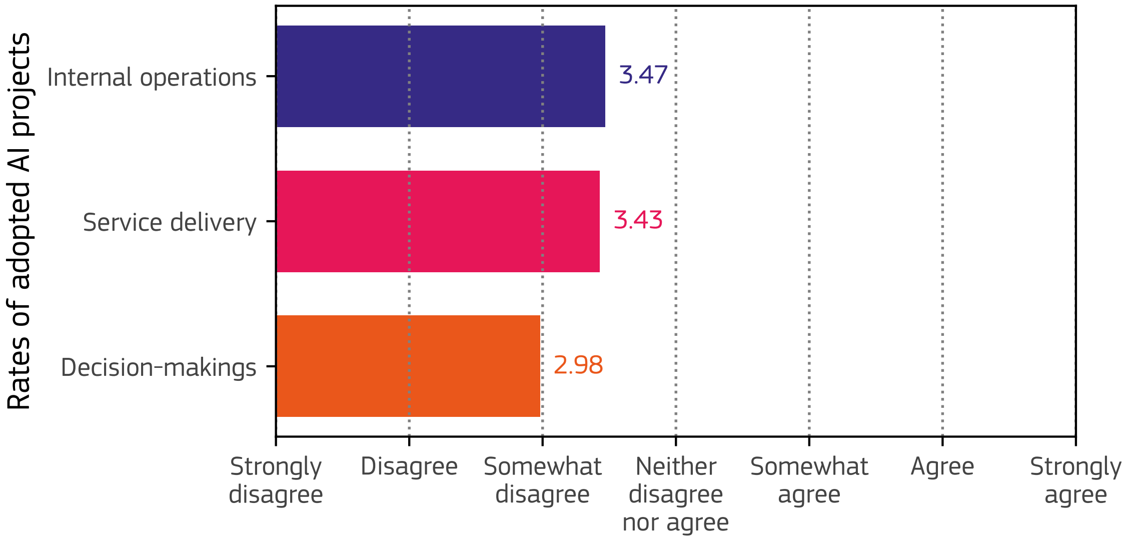
***Source:** JRC own elaboration.*

Figure 2 highlights how public managers in our sample answered the question of how many AI projects they have adopted (fully implemented, blue bars) and the number of projects they have planned (pink bars). Figure 2a shows that 21% of the public managers have no AI projects planned in the near future, a large majority – 63.1% – have one or more projects outlined in the future and 15.8% do not know. The percentages of already adopted AI projects are somewhat lower. Still, as seen in Figure 2b, more than half of respondents (51.8%) indicate that at least one AI application has already been implemented. Around one third (33.7%) say no applications have been adopted and 14.6% do not know. Overall, this indicates that most managers in the public sector have AI projects either planned or already adopted.

Next, and as shown in Figure 3, we will look at the extent to which public managers see AI projects being planned and implemented in various domains. We differentiate between service delivery, internal operations and policy decision-making.

Figure 3

Rates of adopted AI projects on a 7-point Likert scale (including all variables equally), over 3 main specific domains of AI adoption.



Source: *JRC own elaboration.*

Here, we asked not for the number of projects but for the extent to which the public managers agreed that AI was planned/implemented in one of the domains mentioned. More specifically, we asked public managers the following question: 'To what degree has AI been adopted in your organisation in the following areas?' Then the following three areas were listed: service delivery, internal operations and decision-making. They were asked to rate the statement 'We have extensively adopted AI in [domain]' on a 7-point scale, where the lowest point (1) means 'strongly disagree' and the highest point (7) means 'strongly agree'.

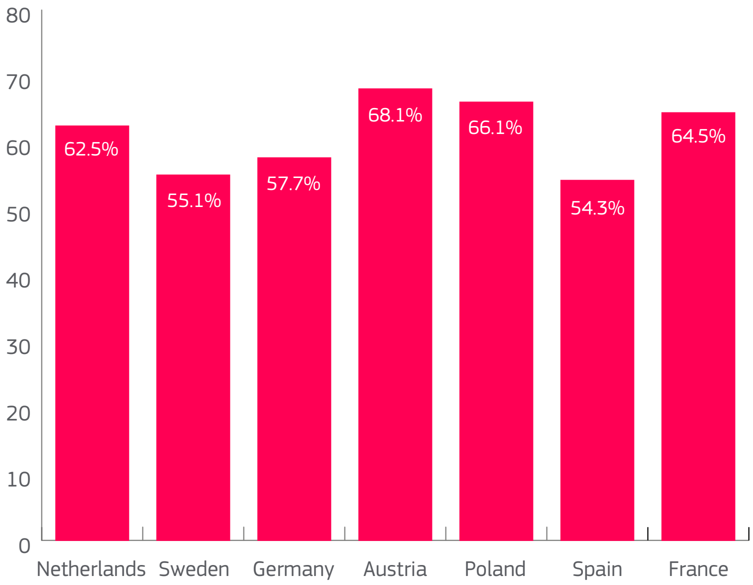
Looking at Figure 3, the higher-scoring areas are perceived as more extensively adopted than lower-scoring areas. Specifically, we can see that adopted projects are at a similar level for service delivery and internal operations, yet there is markedly less AI use in policy decision-making. One explanation might be that human judgement and interpretation are more often needed in policymaking; it is also perhaps harder to find data of high enough quality to support policy-making.

5.2 Comparison of artificial intelligence projects across countries and organisation sizes

Public managers from the following countries were surveyed: Germany, Spain, France, the Netherlands, Austria, Poland and Sweden. This country selection is geographically spread across the EU and is also varied in terms of size and administrative traditions. Figure 4 shows the percentage of managers reporting the implementation of at least one AI project for each country.

Figure 4

Public managers reporting that at least one AI project has been implemented, by Member State.



Source: *JRC own elaboration.*

Figure 4 indicates that there are slight differences by country in the percentage of public managers reporting one or more implemented AI projects. Still, the differences are rather small, and in all countries more than half of the public managers in our survey reported that at least one project had been implemented. Due to the limited sample size for each individual country, it is not possible to make meaningful comparisons, and the data should not be interpreted as setting a benchmark or providing statistically significant indicators of AI adoption in the countries surveyed.

Table 1

Adoption by organisation size.

			Fully adopted and in use				Total
			0	1	2-5	>5	
Organisation size	=<20	Count	7	1	3	1	12
		%	58.3%	8.3%	25%	8.3%	100%
	21-100	Count	31	20	16	9	76
		%	40.8%	26.3%	21.1%	11.8%	100%
	101-400	Count	47	23	36	8	114
		%	41.2%	20.2%	31.6%	7%	100%
	400-2000	Count	42	27	36	10	115
		%	36.5%	23.5%	31.3%	8.7%	100%
	>2000	Count	67	39	47	22	175
		%	38.3%	22.3%	26.9%	12.6%	100%
Total		**Count**	**194**	**110**	**138**	**50**	**492**
		%	**39.4%**	**22.4%**	**28%**	**10.2%**	**100%**

Source: *JRC own elaboration.*

Table 1 shows similar adoption rates for all organisations with more than 20 employees: around 60% of the public managers surveyed reported at least one fully adopted AI project. Among small organisations (20 or fewer employees), we can see that more than half have not yet implemented any AI projects. However, the data on this category should be interpreted with caution, as only 12 managers in our sample work for these small organisations.

5.3 What influences the extent of artificial intelligence adoption?

Finally, we looked at the factors that drive AI adoption. We carried out a regression analysis to determine which factors correlate with AI adoption. In this Science for Policy report, we will not present technical statistical information, only the outcomes of the analysis. Further information on the regression analysis can be found in the Appendix. As highlighted in Chapter 2, we included a range of factors that could affect the level of (perceived) AI adoption. These included technological, organisational and environmental factors, and also factors relating to individual attitudes towards AI. Table 2 provides an overview of which factors have a statistically significant association with perceived AI adoption. The column labelled 'Contributes to adoption' lists the factors that emerged as statistically significant ($p < 0.05$) from the regression analysis. The column 'Does not contribute to adoption' lists the factors that had no statistically significant relation to perceived adoption.

Table 2

Overview of factors that significantly contribute to AI adoption.

Type of factor	Contributes to adoption	Does not contribute to adoption
Technological	Perceived benefits of AI	• AI data capacity • Perceived AI trustworthiness
Organisational	• In-house expertise • Strong AI strategy • Culture open to innovation • Leadership support	Perceived budget
Environmental	Perceived citizen need	• Collaboration with companies • Competition with similar orgs • National government incentives
Attitudinal/Individual		• Positive attitude towards AI • Negative attitude towards AI

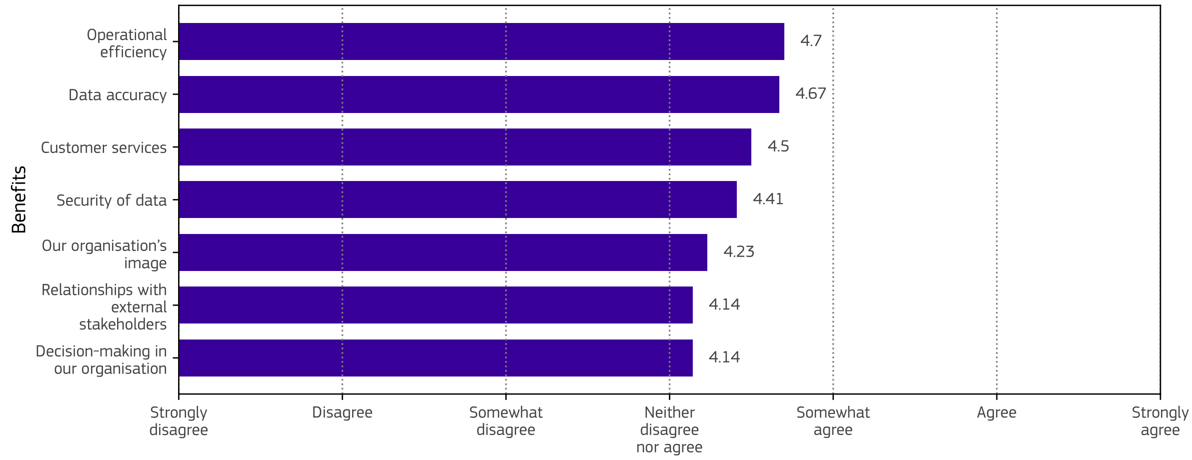
Source: *JRC own elaboration.*

The following six factors contribute to AI adoption: perceived benefits, in-house expertise, an innovative culture, a strong AI strategy, leadership support and perceived citizen pressure. Below we discuss these factors.

1. Perceived benefits of AI. In our survey, 'perceived benefits' refers to the level of recognition of the relative advantage that AI technology could provide to the organisation. Therefore, perceived (direct) benefits would lead to an improvement in the performance of the daily internal processes of the organisation. Public managers who expected that AI would help their organisation to reap benefits such as reducing human workload and improving their image and relations with stakeholders were more likely to have fully implemented AI projects. Figures 5 and 6 provide additional detail on which benefits are particularly expected: managers' main expectation is an increase in efficiency, followed by greater data accuracy.

Figure 5

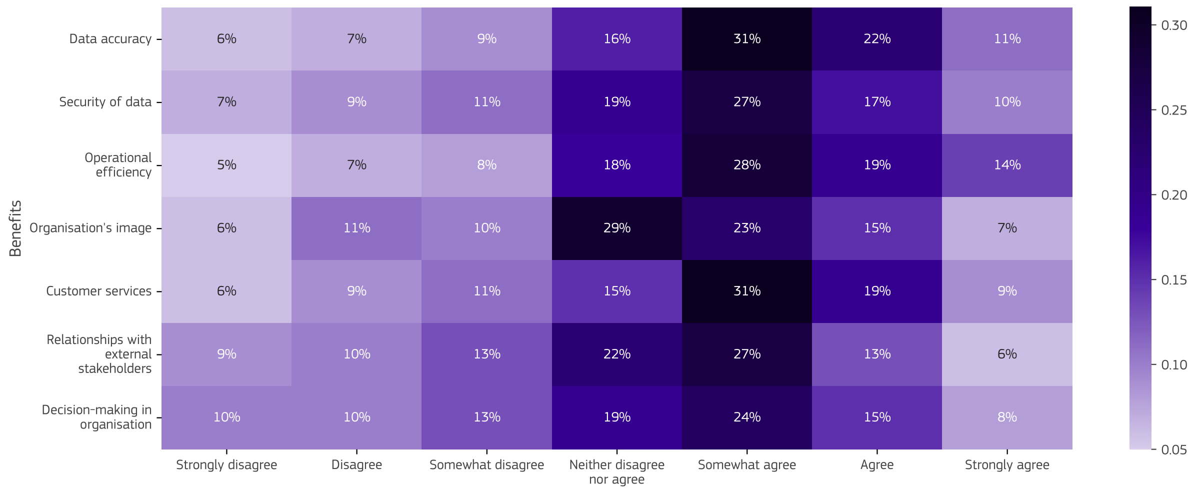
What, now or in the future, is your estimation of the benefits of AI in your organisation? We expect that the use of AI will help us improve... (mean values).



Source: *JRC own elaboration.*

Figure 6

What, now or in the future, is your estimation of the benefits of AI in your organisation? We expect that the use of AI will help us improve...



Source: *JRC own elaboration.*

2. In-house expertise. AI technologies are complex and can be hard to understand for those without technical expertise. In-house capabilities and expertise are needed to develop and implement AI in public organisations. When specific expertise is lacking, it is less likely that AI will be adopted. While this may seem logical, it could be argued that such expertise could be bought in from private companies, which would diminish the need to have the necessary skills in house. However, we found that in-house expertise – for example on legal, technical and ethical aspects of

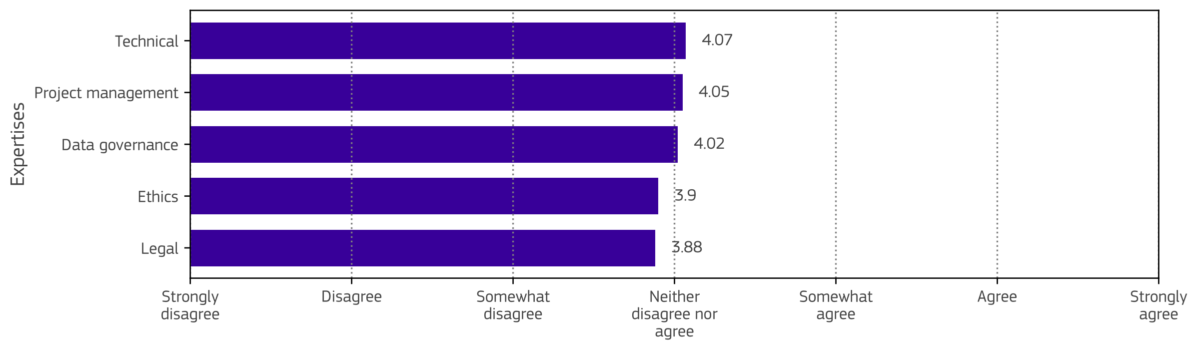
AI – is an important correlate of reported adoption. On the other hand, collaboration with private parties was not a statistically significant factor. This means that the extent to which commercial companies are involved in developing, monitoring and maintaining AI solutions has no significant bearing on perceived AI adoption.

This finding is particularly relevant and underlines the importance of getting expertise on AI into public organisations and not always or only relying on third parties. This is not limited to technical expertise but also related to legal, ethical, governance and project management expertise on AI.

Figures 7 and 8 highlight the specific types of expertise respondents report having in house. A closer look at Figure 7 reveals that – perhaps surprisingly – technical expertise is relatively common, as is expertise on AI project management. Public managers were less likely to report having expertise on supporting functions that should safeguard AI projects, such as legal and ethical expertise.

Figure 7

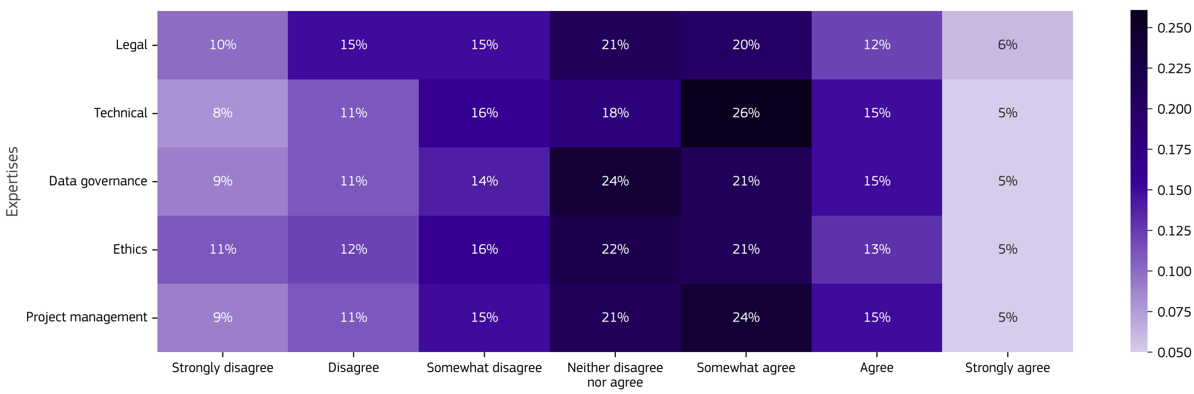
To what extent does your organisation have in-house (AI) expertise on the following? (mean values).



Source: *JRC own elaboration.*

Figure 8

To what extent does your organisation have in-house (AI) expertise on the following?

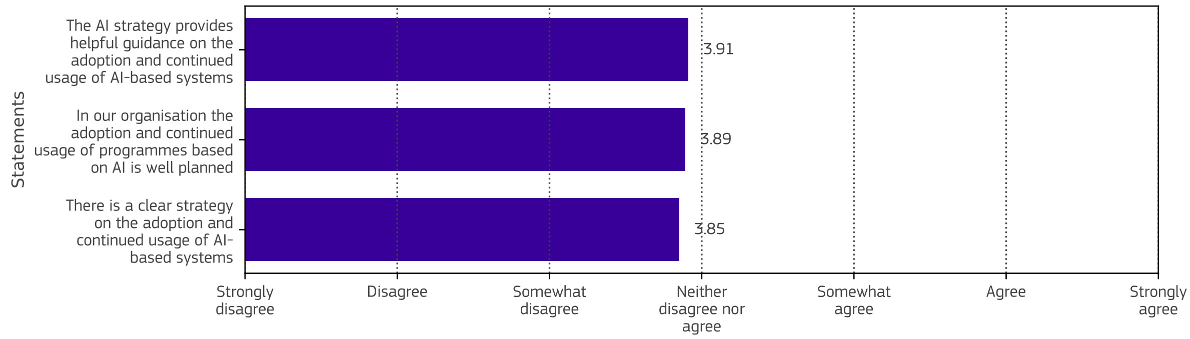


Source: *JRC own elaboration.*

3. Strong AI strategy. Developing a strong and clear strategy is crucial. We found that public managers who indicated that their organisation had **a clear strategy for the adoption of AI-based systems that provided helpful guidance and had well-planned programmes** were more likely to have AI projects implemented in their organisation. This highlights the need for organisations to assess what kind of AI system they need and how this is strategically aligned with their overall mission and goals. Figures 9 and 10 highlight the answers that public managers provided concerning questions on AI strategy. Despite the statistical significance of this variable, most public managers have a rather neutral view of the adoption of an AI strategy within their organisation, and the modal answer category is 'neither disagree nor agree' with an overall mean below 4 out of 7. This observation uncovers a critical gap: while AI strategies seem to play a crucial role in facilitating AI adoption, numerous public administrations either lack such strategies or have strategies that are, in the view of public managers, not sufficiently clear and helpful.

Figure 9

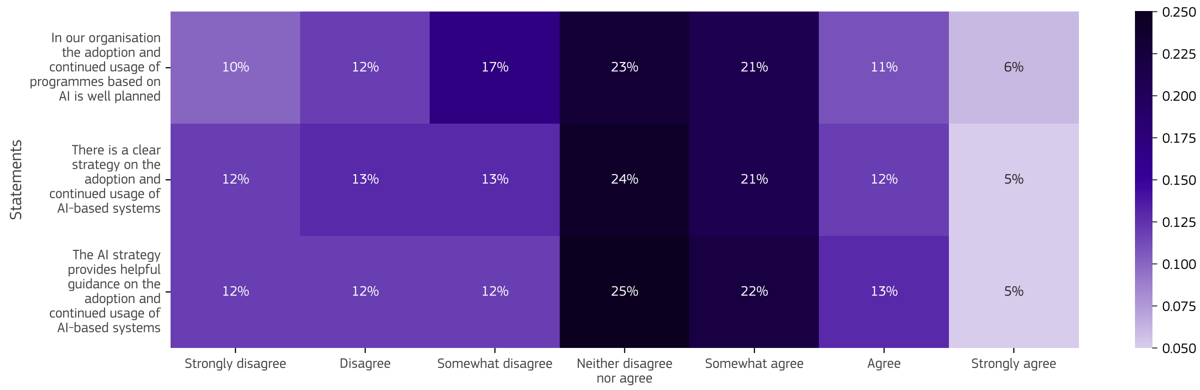
To what extent does your organisation have a strategy for the adoption and usage of AI-based systems? (mean values).



Source: *JRC own elaboration.*

Figure 10

To what extent does your organisation have a strategy for the adoption and usage of AI-based systems?

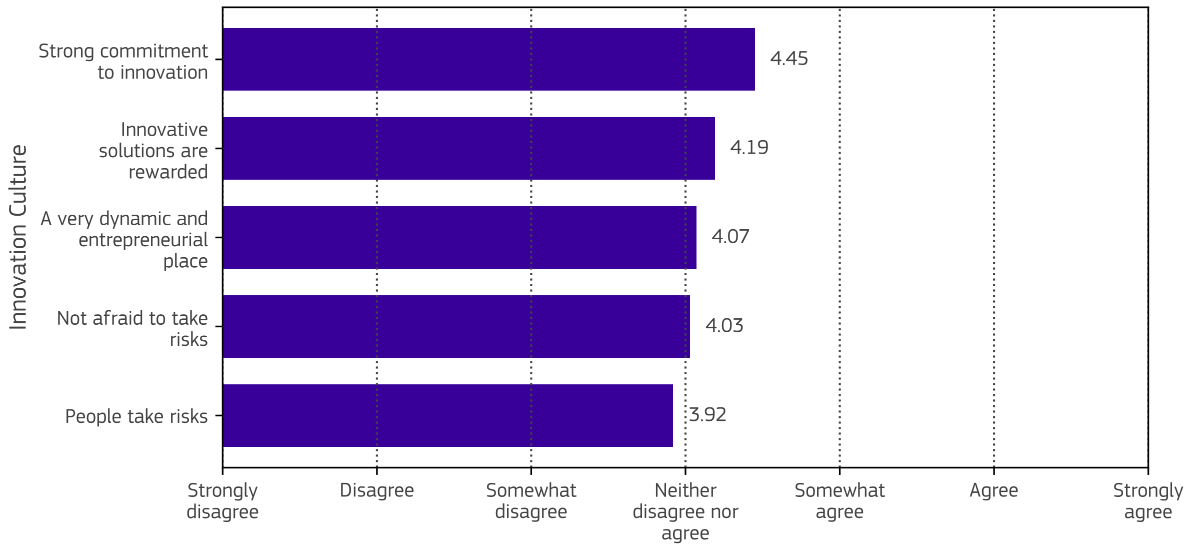


Source: *JRC own elaboration.*

4. Culture conducive to innovation. A category of determinants of technology adoption that is often overlooked relates to the organisation's culture with regard to innovation. Typically, cultures that are receptive to new ideas and willing to take risks are also more likely to adopt novel technological solutions, such as AI. Innovation-oriented governments tend to adopt new AI projects faster because these governments are more likely to see the value of innovations such as AI and adopt them with less resistance. Figures 11 and 12 provide an overview and an in-depth analysis of the extent to which public managers in this study reported an innovation-minded culture.

Figure 11

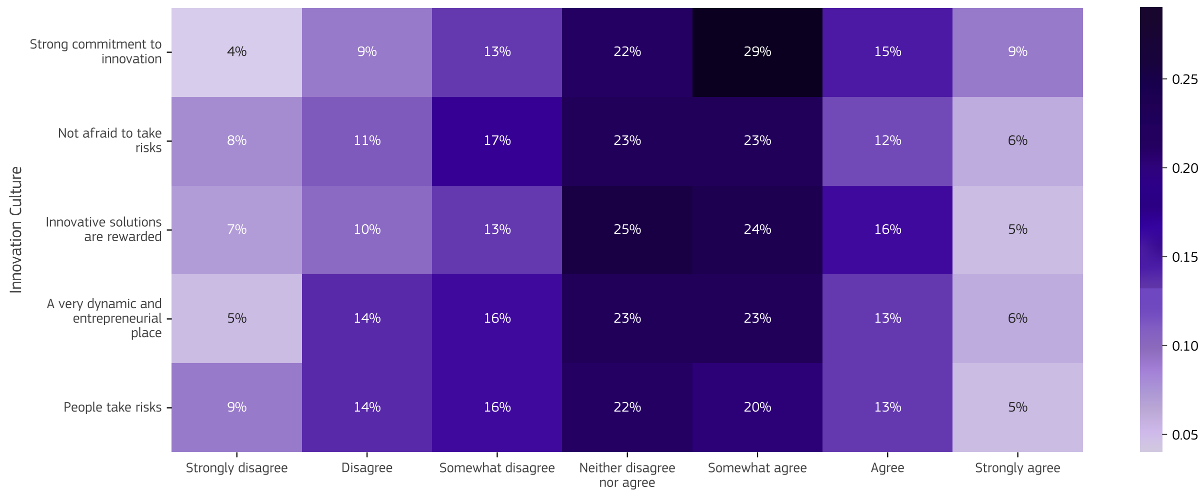
What is the culture in your organisation regarding innovations? (mean values).



Source: *JRC own elaboration.*

Figure 12

What is the culture in your organisation regarding innovations?

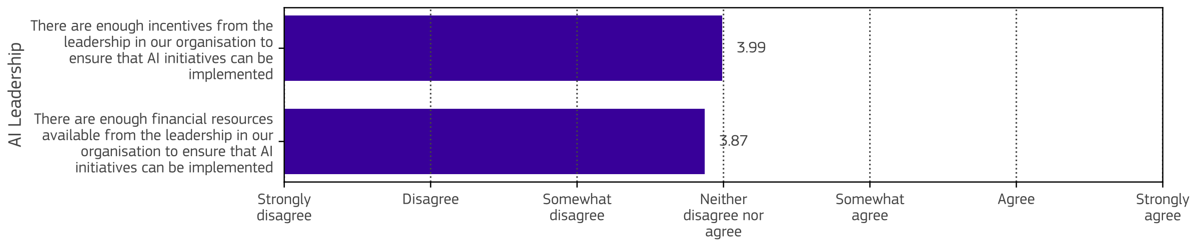


Source: *JRC own elaboration.*

5. Leadership support. This factor is intertwined with the previous one. Leadership that supports innovations is likely to foster an innovative culture. Support can come in the form of words (verbal support), but here we deliberately asked about leadership that offers concrete incentives to implement AI initiatives and/or makes financial resources available to do so. The correlation analysis shows that the presence of such incentives is significant for AI adoption. Figures 13 nd 14 indicate that these aspects of leadership are not deemed entirely satisfactory by the participants in our sample, with the majority of public managers generally expressing disagreement with or neutrality towards the statements provided. This information invites further reflection on ways to enhance this facet, particularly in light of its correlation with the adoption of AI.

Figure 13

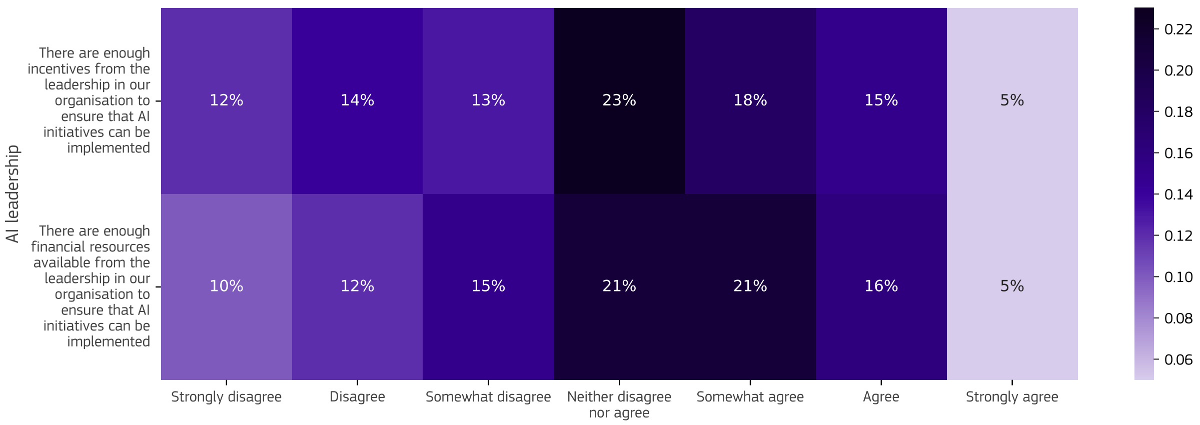
How do you perceive the leadership on AI in your organisation? (mean values).



Source: *JRC own elaboration.*

Figure 14

How do you perceive the leadership on AI in your organisation?

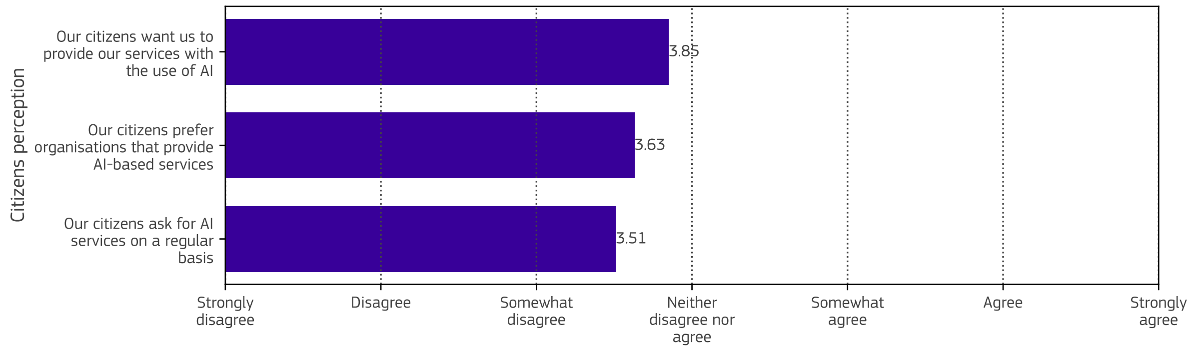


Source: *JRC own elaboration.*

6. Citizen pressure. Public managers also look to the external environment of their organisation. In particular, the need or pressure they feel from citizens is a significant factor for AI adoption. In the case of AI, citizens are using online services and have high standards for their quality and efficiency. Therefore, citizens who interact with the government exert external normative pressure for governments to adopt new technologies to improve such services. Figures 15 and 16 provide more detail on how public managers perceive citizen needs for AI. They are less inclined to perceive explicit requests or preferences for AI services from citizens (3.51) and more inclined to think citizens 'want' those services (3.85).

Figure 15

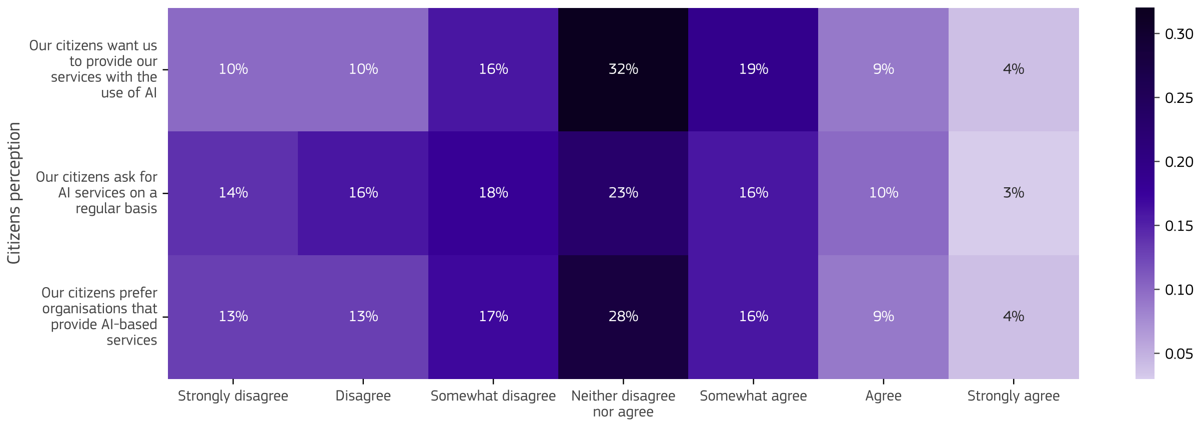
How do you perceive citizen needs for AI in your organisation? (mean values).



Source: *JRC own elaboration.*

Figure 16

How do you perceive citizen needs for AI in your organisation?



Source: *JRC own elaboration.*

6 Conclusions and recommendations

6.1 Conclusions

The central question of this study was **'What technical, organisational, environmental and individual-level factors affect AI adoption in public sector organisations?'**

We have three main takeaways from our findings:

Takeaway 1: AI adoption is no longer a promise; it is a reality, in particular in service delivery and internal operations.

The first conclusion is that most public managers report that their organisations either are planning one or more AI initiatives (63.1%) or have already implemented them (51.8%). On the other hand, around 15% of public managers in our sample do not know the number of planned/implemented projects, around 34% have not (yet) implemented AI and 21% have not reached the stage of planning an AI project. Overall, this means that AI in the public sector is no longer a promise but is becoming a reality. More specifically, AI is planned/implemented in service delivery and internal operations, but not to the same extent in policy decision-making.

Takeaway 2: Organisational factors are driving forces for AI adoption.

We found that, of all factors associated with perceived AI adoption, the organisational factors stand out as driving forces. In part, these are 'softer' aspects of adoption, such as having support from leadership in the form of incentives for AI, and having an innovative culture that is open to new developments. Two other organisational aspects were also correlated with adoption: having a clear AI strategy that includes planning for and guidance on AI implementation, and having in-house expertise on AI. The latter includes not only the technical aspects of AI but also its legal, ethical and governance aspects. Finally, we found that public managers who see the benefits of AI for their organisation, such as improving its efficiency and image, report higher levels of adoption.

Overall, this means that there is no immediate solution when it comes to increasing AI adoption; it is likely that long-term investment in leadership, culture, training and strategic alignment will be required.

Takeaway 3: Anticipated citizen needs are an important external factor in AI adoption.

In addition to taking into account these organisational factors, public managers look at citizen needs and pressure to adopt AI. Surprisingly, other external stakeholders matter less for AI adoption: national government support, competition with other, similar, organisations and collaborations with private companies have less marked effects. Interestingly, overall most public managers do not perceive a high level of demand for AI-powered services from citizens. However, the results show that they are more likely to have adopted an AI project if they believe that citizens want AI-powered services.

6.2 Policy recommendations

Recommendation 1: Pay attention to AI and digitalisation in leadership programmes, organisational development and strategy building.

One of the main findings from our survey was that organisational factors are crucial for AI adoption. This is what we called 'organisational software', a term that encompasses a series of organisational elements that need to coexist to ensure AI adoption. In other words, adoption is a question of getting the organisation's building blocks in place when adopting new technology solutions such as AI. For instance, leadership and strategy should have a vision and support the way AI is used, and this should be carried out and 'felt' in the whole organisation. New technologies are omnipresent and should be integrally taught in leadership programmes. This requires training programmes on digital transformation for public managers, which could show that AI is not a mere technological development but requires organisational change and change management. Here we see interconnections with developing other organisational building blocks, such as building an AI strategy and an open-minded culture.

Recommendation 2: Broaden in-house expertise on AI; this should include not only technical expertise but also expertise on ethics, governance and law.

Our survey found that having in-house expertise is a factor in fostering AI adoption. We found that this extends beyond having technical expertise: in-house expertise on law, ethics and data governance is also influential. Public managers looking to implement AI solutions should therefore seek to hire or train not only data scientists and developers but also those with legal and social science training to ensure a broad range of in-house expertise.

Recommendation 3: Monitor and exchange on citizen needs for digital improvements in government service delivery.

We found that anticipated citizen needs are an aspect of public organisations' external environment that drives adoption. Public managers who perceived citizen needs for AI-powered services reported higher AI adoption rates. To get a better grip on what citizens want and need from AI in government, we recommend monitoring these needs more closely, for instance through focus groups and surveys. In addition, online platforms and discussion forums can be used to enable governments and citizens to exchange ideas. In addition, it is crucial for governments to track how ready citizens are to interact with government through AI-powered services, since the successful implementation of AI hinges on citizens' actual use of and satisfaction with these services. Taking a proactive approach towards citizens' desiderata can enable more responsive ways of adopting AI that is tailored to citizen needs, rather than just aligning with government requirements.

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List of abbreviations and definitions

Abbreviations	Definitions
AI	Artificial Intelligence
DG	Directorate-General (as in EU DG DIGIT)
DV	Dependent variable
EU	European Union
JRC	Joint Research Centre
INNPULSE	Innovation of Public Services and Digital Transformation of Governance
IT	Information Technology
ML	Machine Learning
p	p-value (used in statistical context, e.g., $p < 0.05$)
PSTW	Public Sector Tech Watch
TOE	Technology–Organization–Environment (framework)
TSI	Technical Support Instrument

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Annexes

Annex 1. Full questionnaire

Welcome to a study of the Public Sector Tech Watch, a research project by the European Commission. We are studying the adoption of artificial intelligence in the public sector. Your expertise is required so we can learn more about its use in your organisation. By completing this questionnaire you will contribute to our understanding of AI in the public sector and help the European Commission to identify possible recommendations for public organisations.

You **don't have to be an AI expert** to fill out this survey! It will take about **15 minutes** to complete the questions.

Please take the time to read the following important information to make sure you understand what it means to participate and how we will secure your data.

This questionnaire is completely anonymous, and we do not track any IP addresses. We kindly ask you to avoid including any personal information that could potentially disclose your identity in the open text field of the survey.

Introduction – what is AI?

We are interested in **the use of AI** in the organisation that you are working for.

Please carefully read the following definition of AI before you start the questionnaire:

We define AI as *the ability of a machine to display human-like capabilities such as reasoning, learning, planning and creativity. AI applications can be found in, for instance: virtual assistants, image analysis software, search engines, speech and facial recognition systems*.

Start of survey (pre-survey filter questions)

Within which sector are you currently working? (single choice)

- Private sector (→ end of survey)
- Public sector – including municipalities, central and regional government
- Public sector – including public agencies
- Healthcare sector (→ end of survey)
- Education sector (→ end of survey)
- Nonprofit sector (→ end of survey)
- Other sector (→ end of survey)
- I'm currently unemployed (→ end of survey)

Which of the following best describes your primary role in the organisation for which you work?

- Executive / senior management
- Middle management / line management / supervisory
- Individual contributor / non-management

What is the domain your organisation predominantly operates in?

- Defence
- Economic affairs
- Education
- Environmental protection
- General public services
- Health
- Housing and community amenities
- Public order and safety
- Recreation, culture and religion
- Social protection

Which of the following best describes your primary role in the organisation for which you work?

- Local
- Regional
- National
- Other (Please specify)

What is the number of employees working in your organisation? Here we are interested in the overall organisation, not just your team or department.

AI goals and adoption

Let's get started.

Please pay attention when completing the survey.

- Where the questions say 'organisation', you can **also think about your team or department** when answering the questions if you feel more confident doing so.
- We are interested in the perceptions you have of **your situation. This means there are no right or wrong answers**.

To the best of your knowledge, to what degree has **AI been planned** in your organisation in the following areas?

We are **planning** to use AI

- in **providing services to citizens**
- in our **internal operations**
- in our **policy decision-making**

[1 – Strongly disagree, 2 – Disagree, 3 – Somewhat disagree, 4 – Neither disagree nor agree, 5 – Somewhat agree, 6 – Agree, 7 – Strongly agree]

To what degree has **AI been adopted** in your organisation in the following areas?

We have extensively adopted AI

- in **providing services to citizens**
- in our **internal operations**
- in our **policy decision-making**

Please indicate your estimation of the **number of projects or solutions** that use AI in your organisation.

Planned/in development:

- 0
- 1
- 2–5
- More than 5
- I don't know

Fully adopted and in use:

- 0
- 1
- 2–5
- More than 5
- I don't know

Expectations of AI

What is your estimation of the benefits of AI in your organisation, now or in the future?

I expect that the use of AI will help us to improve

- data accuracy
- data security
- the reduction of human workload
- our organisation's image
- customer services
- relationships with external stakeholders
- decision-making in our organisation

Data quality

Please [select] here your best estimation about **data usage in your organisation**.

- We have access to **good quality** data for analysis
- We can manage **large amounts** of data
- We have a strong and clear **data strategy**

What is your attitude towards **how AI operates in your organisation**?

Generally speaking

- I believe that AI in our organisation can be **trusted**
- AI in our organisation uses **accurate data**

- AI in our organisation gives **desired outcomes**
- AI in our organisation can be **relied upon**

Expertise and innovation

What is the role of **commercial companies** in developing AI in your organisation **in general**?

- They are **proactive** and come with new solutions
- They have a very **strong involvement** in developing and implementing the solution
- They **monitor and maintain** the solution over time

To what extent does your organisation have **in-house expertise** on the following?

- **Legal** expertise in AI
- **Technical** expertise in AI
- **Data governance** expertise in AI
- **Ethical** expertise in AI
- Expertise on **project management** in AI

What is the **culture** in your organisation regarding **innovations**?

- My organisation has a strong **commitment** to innovation
- Most people in my organisation are **not afraid to take risks**
- People who develop innovative solutions to problems are **rewarded**
- My organisation is a **very dynamic and entrepreneurial** place
- People are willing to stick their necks out and **take risks**

Funding and strategy

- What is your attitude towards the funding of AI projects in your organisation?

We have **enough funding** to ...

- **develop new** AI in our organisation
- **keep AI running** in our organisation
- **train employees** to use AI in our organisation

To what extent does your organisation have a **strategy** for the adoption and usage of AI-based systems?

- In our organisation the adoption of programmes based on AI is **well-planned**
- There is a **clear strategy** on the adoption of AI-based systems
- The AI strategy provides **helpful guidance** on the adoption of AI-based systems

Incentives for AI adoption

How do you perceive the **leadership on AI** in your organisation?

- There are enough **incentives** from the leadership in my organisation to ensure that AI initiatives can be implemented
- There are enough **financial resources** available from the leadership in my organisation to ensure that AI initiatives can be implemented
- There is a great deal of **resistance** from the leadership in my organisation towards implementing AI initiatives

How would you estimate the level of AI adoption in **other** organisations that are **similar to your own**?

[0 = others have much less AI adoption, 5 = others have the same AI adoption, 10 = others have much more AI adoption]

Support and need for AI

Does **national government support the use of AI** in your organisation?

Remember that these questions are about your estimation; there is no right or wrong.

- National government provides a robust **ethical framework** for the use of AI in public organisations
- National government provides sufficiently clear **official policies** on the use of AI in pub-lic organisations
- National government provides clear AI policies on **data security and protection** in pub-lic organisations

How do you perceive **citizens' need** for AI in your organisation?

- Citizens **want** us to provide our services with the use of AI
- Citizens **ask** for AI services on a regular basis
- Citizens **prefer** organisations that provide AI-based services

AI in society

Now, we would like to ask you [for your] personal opinions about **AI in society more broadly**.

These questions are no longer about the organisation you work for.

- I am interested in using AI systems in my **daily life**
- I think **public organisations** tend to use AI **unethically**
- There are many **beneficial applications** of AI
- I think AI is **dangerous**
- I think **private companies** tend to use AI **unethically**

Final questions

This is the final page of this questionnaire.

Please be reminded that the results of this survey can never be traced to you as an individual.

How **informed** would you say you are about AI in the organisation you work for? Answer on a scale from 0, 'not at all informed', to 100, 'fully informed'.

How **long have you been working** for your current organisation (in any position)?

- 5 years or less
- 6–10 years
- 11–15 years
- 16–20 years
- 21 years or more

How **old** are you?

- Below 30 years old
- 31–40 years old
- 41–50 years old
- 51–60 years old
- More than 60 years old

How many **people** do you manage in your current supervisory role?

- Less than 5
- 5–10
- 11–20
- 21–30
- More than 30
- Prefer not to say

Annex 2. Regression table

We carried out an ordinary least squares regression to analyse the factors that contribute to perceived AI adoption. The full analysis is shown below.

	adoptedAI	adoptedAI	adoptedAI	adoptedAI	adoptedAI
Predictors	Std. beta	Std. beta	Std. beta	Std. beta	Std. beta
(Intercept)	– 0.00	– 0.00	– 0.00	– 0.00	0.03
benefits	0.30***			0.23***	**0.22*** **
datacap	– 0.01			– 0.11**	**– 0.09***
trustwAI	0.34***			0.09	0.09
expertise		0.17***		0.14**	**0.13***
culture		0.17***		0.11*	**0.10***
budget		– 0.03		– 0.03	– 0.02
AIstrat		0.27***		0.19***	**0.18** **
leader		0.14**		0.11*	**0.12***
private			0.18***	– 0.03	– 0.03
competition			0.04	0.02	0.01
natgov			0.25***	0.04	0.04
citneed			0.30***	0.14***	**0.13** **
AIattpos			– 0.02	– 0.11**	**– 0.10***
AIattneg			0.02	0.03	0.01
Observations	576	576	576	576	576
R2 / R2 adjusted	0.320/0.316	0.410/0.405	0.362/0.356	0.474/0.461	**0.490/0.470**

NB: * p < 0.05, ** p < 0.01, *** p < 0.001. Includes controls: country dummies, function, organisation size (all not significant in final model).

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