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AI READINESS INDEX IN THE PUBLIC ADMINISTRATION

National
Study



2026

Institute of Public Administration

National study

ARTIFICIAL INTELLIGENCE READINESS INDEX
IN THE PUBLIC ADMINISTRATION IN
THE REPUBLIC OF BULGARIA
2026

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Summary

The adoption of artificial intelligence (AI) in the public sector is advancing faster than the development of institutional frameworks that should guide it. The principal challenge facing public administrations is not just technological, but above all organisational. It concerns institutions' ability to adapt their rules and processes and to develop the capacity required for a technology that is already becoming part of the day-to-day work of some employees.

This study presents the second national AI Readiness Index survey of the public administration of the Republic of Bulgaria and compares for the first time the results of two consecutive survey rounds conducted in 2025 and 2026. The Index is a composite indicator combining organisational readiness, weighted at 65%, and employees' individual capacity, weighted at 35%. The data were collected through an online survey of 5,475 respondents from institutions at central, district, and municipal levels in June and July 2026.

The overall Index score rises from 45 to 49 out of 100, while the readiness of the Bulgarian administration remains at the 'developing capacity' stage. Practical use and reported willingness to participate in AI applications have a more pronounced change than perceived organisational readiness. Regular or limited use increases from 12.3% to 18.1%, while willingness to engage in practical work with AI rises from 44.7% to 56.6%. The share of positive ratings of organisational readiness to implement AI increases from 11.1% to 12.5%.

Individual capacity improves across all twelve measured indicators. At the same time, the gap between practical skills and the skills required to manage and direct the use of AI widens from approximately 3.6 to 6.7 percentage points. A similar divergence is observed in preparations for implementation of the Artificial Intelligence Act (AI Act). Awareness of its requirements has a marked increase, while indicators related to concrete compliance actions remain below 12%.

There is a particularly notable mismatch between individual access to AI and the institutional mechanisms for its use and for knowledge sharing. Nearly one third of respondents, 29.8%, use a personal account without institutional approval, while 11.7% report at least one institutionally supported means of access. Only 3.5% report systematic exchange of knowledge and good practices, and 9.9% report active institutional support for experimentation. Individual use of AI is already expanding, but still rarely develops into shared organisational knowledge and sustainable institutional practice. The main barriers are the absence of clear internal rules, security concerns, and limited access to appropriate tools.

The results show that AI readiness should be understood primarily as a capacity for institutional adaptation rather than a simple availability of technological resources. Compared with 2025, the need for awareness and training is now accompanied by a need

for clear rules, assigned responsibilities, secure access, and mechanisms for institutional learning.

The Index measures perceived organisational readiness and individual capacity within the public administration. It is not an international ranking of Bulgaria and should not be compared directly with indices assessing national artificial intelligence ecosystems.

Introduction

This study presents the results of the second national Artificial Intelligence (AI) Readiness Index survey in the public administration. Comparison with the 2025 results (Ivanov, P., Ivanova-Chikova, T. & Stefanov, S. (2025)) allows tracking of the main directions of change in attitudes, knowledge, and practices. It does not track the same individuals over time, comparing instead two independent national surveys. The study treats AI readiness as a management capability that depends not only on technological availability, but also on rules, data, competences, responsibilities, and institutional learning mechanisms.

A similar approach is used in international frameworks for assessing AI readiness and maturity. The OECD.AI Index supports evidence-based policymaking and the monitoring of progress towards trustworthy AI (OECD, 2026b, pp. 3, 13). UNESCO's maturity framework for public administrations does not define a single 'correct' level; rather, it supports organisations in assessing their current position, identifying the desired direction of development, and planning the steps required to reach it (UNESCO, 2025, p. 7). This logic is consistent with the conceptual basis of the present Index.

The UNESCO framework further shows that organisational maturity for AI is multidimensional. It encompasses six interconnected areas: strategy and value; people and organisational culture; technology and infrastructure; AI operations and ecosystem; governance, ethics and risk; and data. Technological readiness is therefore only one of the prerequisites for sustainable implementation. Leadership, organisational structures, competences, change management, the legal and ethical framework, and the ability to prepare and use data for specific AI applications are equally important (UNESCO, 2025, pp. 7–8).

The OECD.AI Index follows a similar logic, considering national AI capacity through a combination of the policy and governance environment, infrastructure, knowledge and skills, research and development, and international cooperation. These approaches share the common understanding that readiness does not arise from the presence of a single resource, but from the ability of different institutional conditions to work together and be converted into sustainable outcomes (OECD, 2026b, pp. 3, 14–15).

Public sector research shows that AI implementation should not be treated as a standalone information and technology project. It simultaneously changes the technical and social conditions of work, including organisational processes, roles, practices, and responsibility models (Tangi et al., 2025, pp. 1–3). The Index therefore treats policies, data, skills, organisational practices, governance, and institutional learning as interconnected conditions for the sustainable use of AI, rather than separate elements of digitalisation.

The key question is no longer whether public administrations will use AI, but whether they have the capacity to use it in ways that improve administrative services and analytical work without weakening accountability. The Organisation for Economic Co-operation and Development (OECD) finds that AI use is more prevalent in internal

operations and public-service delivery than in government oversight and policymaking; it also stresses that ‘unlocking AI’s benefits requires mitigating its risks’ (OECD, 2025, p. 9). In the context of public administration, this means that technology can and should improve governance, but cannot replace public responsibility for setting objectives, establishing rules, and making decisions.

In 2026, the scope of the study was expanded to include questions on institutional learning and organisational practices. This makes it possible to assess not only whether individual employees use AI, but also the extent to which administrations turn accumulated experience into shared knowledge, common rules, and sustainable organisational capacity. Research on organisational learning in the public sector also shows that sustainable technological change depends on institutions’ capacity to absorb experience, adapt their practices, and apply accumulated knowledge to subsequent decisions. In the context of AI, this includes not only the development of individual knowledge and skills, but also the organisation’s ability to select appropriate applications, manage risks, and create conditions for responsible experimentation.

On this basis, the present study aims to assess changes in organisational readiness and individual capacity between 2025 and 2026 and to establish the extent to which growing use of AI is being transformed into institutionally supported, shared, and responsibly governed practice.

Study methodology

The AI Readiness Index is a composite self-assessment indicator designed to measure perceived organisational readiness and individual capacity for the use of artificial intelligence in public administration. It comprises two main components:

- Organisational readiness, covering respondents’ assessments of the existence of policies, infrastructure, organisational practices, and management support for the use of AI.
- Individual capacity, covering employees’ self-assessed knowledge and skills for the practical and responsible use of AI, as well as for managing and steering its implementation.

The two components were measured through an online questionnaire comprising groups of questions in the relevant thematic areas. Responses were coded as numerical values according to a predefined scheme and aggregated into two separate scores for organisational readiness and individual capacity. After conversion to a scale from 0 to 100, the overall Index score is calculated using the following formula:

- $\text{Index} = 0.65 \times \text{organisational readiness} + 0.35 \times \text{individual capacity}$

The weights assigned to the two components were established when the methodology was developed in 2025 based on the conceptual assumption that individual knowledge and skills can contribute to sustainable AI use only when supported by institutional rules,

resources, and management mechanisms. They represent a predefined methodological choice rather than a statistical estimate of the relative causal influence of the two components.

The overall score is presented on a scale from 0 to 100 and interpreted through four analytically defined readiness levels. The boundaries between them have a descriptive and indicative function. They should not be treated as statistically established thresholds or as evidence that all administrations within a given interval share the same characteristics.

The methodology follows the general logic of international frameworks for assessing organisational maturity without reproducing their indicators or calculation methods. The UNESCO framework defines self-assessment as an evidence-based process that should take account of strategic, operational, technical, legal, and domain-specific perspectives (UNESCO, 2025, p. 9). It is used here as a conceptual reference point for interpreting organisational readiness, not to calibrate or validate the numerical values of the present Index.

The Index also differs from international indicators that assess national artificial intelligence ecosystems. The OECD.AI Index, for example, measures the implementation of national policies across five areas: research and development, enabling infrastructure, the policy environment, jobs and skills, and international cooperation (OECD, 2026b, pp. 3, 13). Its unit of analysis is the national ecosystem, whereas the present Index measures the perceptions and self-assessed capacity of public administration staff. Because the two indices differ in their object of analysis, data sources and calculation methods, their numerical values are not directly comparable.

The construction of the Index does not equate more extensive use of AI with a higher degree of readiness. The availability and frequency of use of technological tools are assessed alongside the conditions under which such use takes place, including rules, organisational capacity, data, management mechanisms, and opportunities for institutional learning. Technological presence is thus distinguished from institutionally supported and sustainable implementation of AI.

The readiness levels are defined as follows:

- 0–39: Initial stage of development – foundational work and strategic planning are required.
- 40–64: Developing capacity – the foundations are taking shape; further development through training and resource support is required.
- 65–84: Functioning capacity – the administration is already using AI and has active mechanisms for its implementation.
- 85–100: Strategic maturity – AI is integrated into governance and processes; institutions act as leaders and drivers of innovation.

The Index as a tool for institutional improvement

The Index was also developed as a tool to help administrations assess their current position, monitor changes over time, and identify areas in which further action is required for the introduction of AI.

The Index is not intended to replace in-depth institutional analysis and does not, by itself, establish the causes of the reported results. Rather, it provides a general diagnostic basis for discussing and planning the development of organisational capacity at different levels.

In line with this purpose, both in 2025 and 2026 IPA provides individual reports to administrations that meet the predefined criterion for sufficiently broad participation. In 2026, institutions that requested access to their own results also receive anonymised microdata from the study.

The provision of institutional results is based on the understanding that adapting to AI requires each administration to have not only an overall view of the public administration, but also information about its own organisational conditions. The data can help identify areas for improvement, support more open and evidence-based internal discussion of the results, and inform the formulation of priority actions. Whether administrations actually use the information provided in this way, however, depends on subsequent management decisions and cannot be established solely from the Index results.

This function of the Index is consistent with the regulatory framework for quality management in the administration. The Administration Act establishes continuous quality improvement as a principle of administrative activity and provides for total quality management to support the effective and efficient achievement of strategic and annual objectives. The definition of a quality management system also includes the use of appropriate analytical tools, taking account of the specific nature of the activity and stakeholder needs. The Index can support this diagnostic function in the field of AI readiness but does not constitute a comprehensive quality management system by itself.

The practical logic of the Index is conceptually close to the cycle of organisational self-assessment and improvement applied through the Common Assessment Framework (CAF): assessing the current situation, identifying areas for development, defining priority actions, and subsequently monitoring progress. The Index has a narrower thematic scope and should be regarded as a complementary diagnostic tool in the field of AI readiness, not as part of CAF or its methodological extension. A similar diagnostic function is performed by IPA's institutional self-assessment model 'Is Your Administration a Learning Organisation?', which focuses on organisational culture, learning mechanisms, and internal knowledge exchange.

Viewed as complementary tools, the AI Readiness Index, CAF, and the learning-organisation self-assessment can help connect measurement with organisational learning and action planning for improvement. This understanding is also consistent with the broader concept of the learning organisation. The mere availability of information about an organisation's current state does not automatically lead to improvement. Value arises

when results are used to make sense of problems collectively, reconsider established practices, and take subsequent action. In this sense, self-assessment matters not as a one-off measurement but as an organisational inquiry that responds to mismatches between expected and actual outcomes and it can contribute to the development of what Senge describes as ‘an organization that is continually expanding its capacity to create its future’. (Senge, 1990, p. 14; Argyris & Schön, 1996, p. 16).

It has not yet been examined whether the provision of institutional reports and data leads to subsequent changes in administrations’ rules, practices or capacity. Assessing how institutions use the results, and the possible relationship between feedback and subsequent organisational development, constitutes a separate research question for future editions.

Scope and sample

The survey was conducted from 19 June to 17 July 2026. A total of 5,475 employees from institutions at central, district, and municipal levels across the country took part. Participants differed by sex, age, position, and length of service, ensuring broad coverage. However, the results should be interpreted as self-assessments by participating employees and do not constitute a probability-based representative estimate for each individual administrative structure. The comparison with 2025 is between two independent surveys and does not track the same individuals over time. The larger share of participants from Sofia City District is expected, given both the size of the capital and the centralised structure of the public administration.

The collected data were analysed quantitatively (distributions, means and proportions) and visualised through a series of charts. The following figures present the distribution of respondents by sex, age, position, and length of service in the administration.

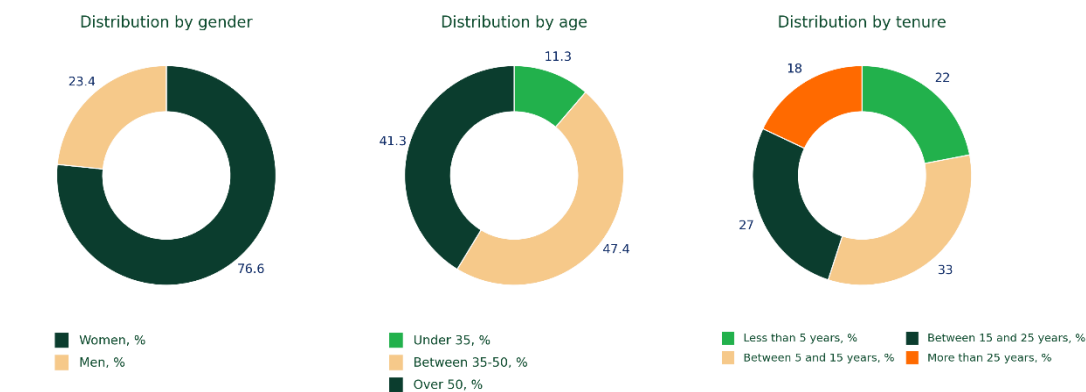


Figure 1. Distribution by gender, age and length of service

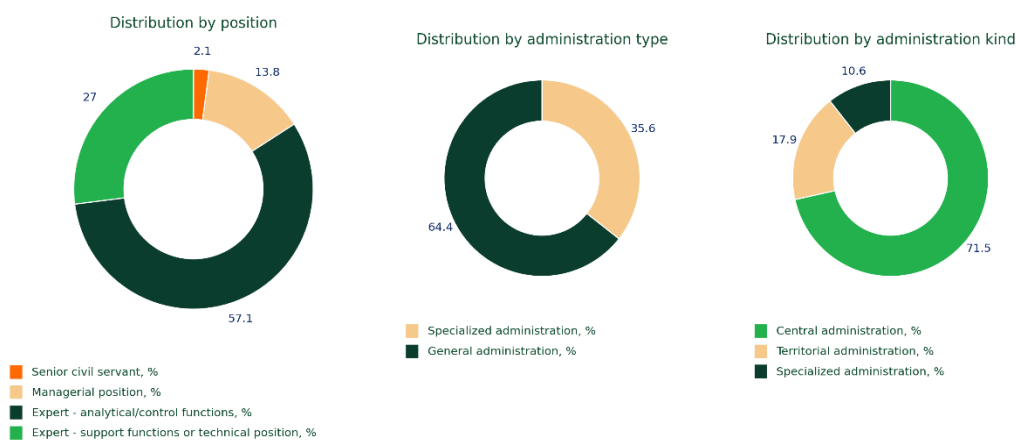


Figure 2. Distribution by post, type and category of administration

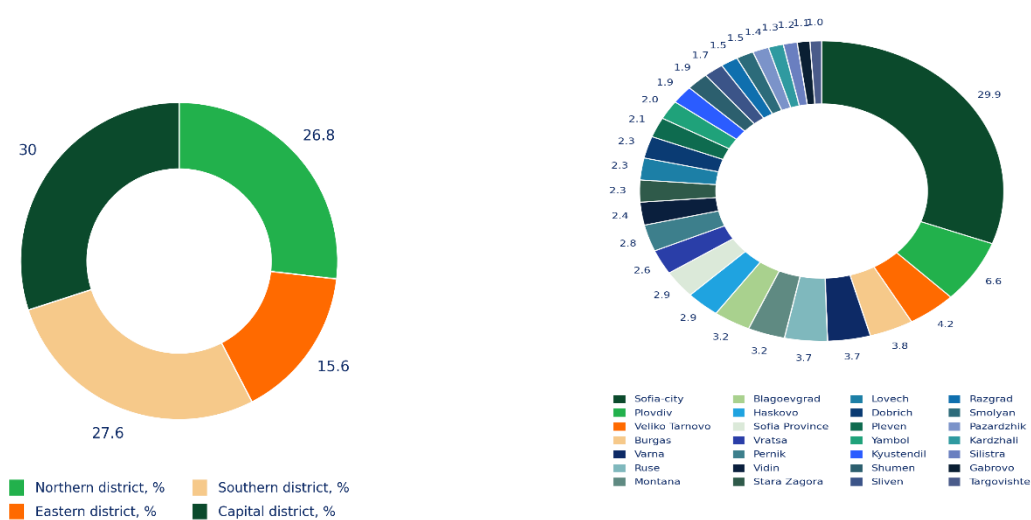


Figure 4. Distribution by district

Figure 3. Distribution by region

CHAPTER 1

AI READINESS

INDEX

IN PUBLIC

ADMINISTRATION



I. Organizational Readiness

Attitudes and Practices Regarding the Development and Use of Artificial Intelligence

in the public administration



Organisational readiness is improving, but for most indicators the change remains within a few percentage points. The two measurements do not allow a reliable forecast of the future pace of development, but they do show that the distance to the 'Functioning Capacity' level remains substantial.

The least developed areas continue to be those related to adopting clear internal rules, designating responsible persons, and introducing documented procedures. Some indicators relating to infrastructure and the organisational environment have improved, but preparations for implementing the Artificial Intelligence Act continue to show the clearest mismatch between awareness and concrete action.

This pattern is consistent with UNESCO's maturity framework for public administrations, according to which effective organisational structures should provide clearly assigned accountability for AI initiatives, the necessary expertise and consistency across the organisation (UNESCO, 2025, p. 21). From this perspective, defining roles, responsibilities and procedures is not an ancillary element of technological implementation, but an integral part of institutional readiness.

Similar difficulties have also been identified in an OECD comparative analysis of the use of AI in core government functions. These include skills shortages, limited access to high-quality data and opportunities for data sharing, a lack of concrete guidance for translating strategic intentions into practical action, and insufficiently developed monitoring and evaluation mechanisms (OECD, 2025, p. 10). The Bulgarian data show a similar mismatch between growing interest in AI and the institutional conditions required for its secure and responsible use.

This problem is not specific to Bulgaria. An international comparative analysis concludes: 'The results of our study show that while AI-enabled policy actions are steadily entering policymaking, their institutionalization remains uneven and fragmented' (Lnenicka et al., 2026, p. 5). The Bulgarian results add to this broader picture by showing that employees' readiness to use AI is increasing faster than the development of the formal conditions required for its secure, consistent, and responsible implementation.

I.1 Internal policies on artificial intelligence



Figure 5. Internal policies on artificial intelligence

In 2026, positive ratings increase across all five indicators. The strongest growth is in management support (+7.2 percentage points), followed by identified AI use cases (+6.1 percentage points) and the existence of a concept or vision (+4.8 percentage points). Despite the improvement, positive ratings remain below one third for every indicator, providing no basis to assert that an institutional AI framework is widely established.

The share of neutral responses decreases across all five indicators, but this does not lead solely to an increase in positive ratings. For 'budget and resources', disagreement rises by 3.3 percentage points, while for 'policies and ethical guidelines' it rises by 2.8 percentage points. This indicates a clearer differentiation of assessments but does not in itself demonstrate greater awareness or more realistic judgement.

There is an asymmetry between the development of support and the development of resource provision. Management support increases by 7.2 percentage points, whereas positive ratings of the availability of budget or resources increase by 2.0 percentage

points. If this divergence persists, management expectations may develop faster than the resource capacity required to realise them.

The results indicate that the positive trend in vision and management support has not yet reached a level at which strategic intent systematically shapes organisational decisions. This distinction is also clear in the UNESCO framework. At the earliest maturity level, AI initiatives are predominantly opportunistic and do not form part of an overall organisational vision. At higher levels, the vision is linked to measurable objectives, is actively supported by management and influences the selection of initiatives, the allocation of resources, and organisational planning (UNESCO, 2025, pp. 13–15).

From this perspective, the increase in positive ratings of management support in 2026 is an important precondition for development but does not amount to institutionalised strategic readiness. The significance of management support extends beyond the formal approval of initiatives. In Senge's account of the learning organisation, a genuine shared vision enables 'people excel and learn, not because they are told to, but because they want to' (Senge, p. 9, 1990). Management support therefore acquires organisational significance when it is translated into understandable priorities, consistent decisions, and conditions that enable employees to participate in developing new practices. The next step is for management support to be converted into concrete priorities, responsibilities, adequately resourced plans, and mechanisms to monitor results.

I.2 Data and technological infrastructure

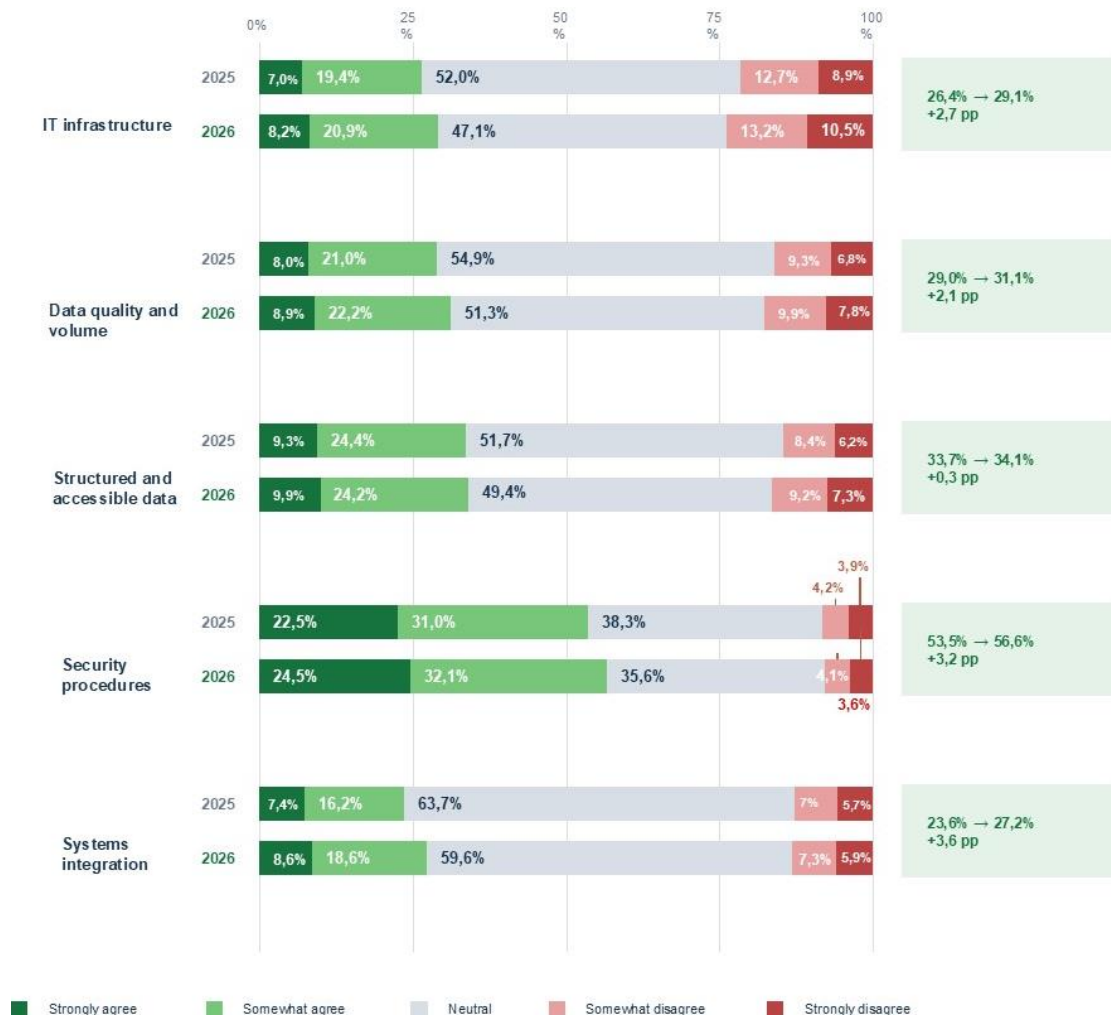


Figure 6. Data and technological infrastructure

As in 2025, this pillar records the highest values within the organisational component. The share of positive ratings of security procedures reaches 56.6%, compared with 53.5% in 2025, and remains the only indicator with aggregate agreement above 50%. This result probably reflects the existence of established general frameworks for information security and data protection rather than necessarily indicating policies developed specifically for the use of AI.

Despite the overall improvement, indicators relating to data readiness and system integration remain at substantially lower levels. The share of positive ratings for structured and accessible data is virtually unchanged (+0.3 percentage points), while the shares for the quality and volume of data and for IT infrastructure increase by 2.1 percentage points and 2.7 percentage points, respectively. The share for system

integration increases by 3.6 percentage points but, at 27.2%, remains the lowest in the pillar.

These results indicate that the existing technological foundation is not yet sufficiently developed to support more extensive embedding of AI in administrative processes. Limited integration and insufficiently well-managed data may impede the transition from the use of general-purpose language models for text-based work and search to applications for analysis, process support, and service improvement.

A practice-oriented international study from 2025 emphasises that AI rarely creates value as a standalone tool. More substantial results are achieved when employees with relevant domain expertise use AI at appropriate stages of the workflow (McKinsey, 2025, p. 22). In this context, the low level of system integration in the Bulgarian administration emerges as one of the constraints on moving from isolated applications towards more sustainable use of AI in analysis, processes, and service delivery.

The comparatively better results for data and infrastructure should not be interpreted as equivalent to overall AI readiness. In the UNESCO framework, data and technological infrastructure are two separate pillars alongside strategy, people and culture, operations, and risk management. This underscores that a sound digital foundation is a necessary but insufficient condition for organisational maturity (UNESCO, 2025, pp. 7–8).

UNESCO also draws a further distinction between the availability of data and their actual fitness for use by AI. At lower levels of maturity, problems of quality and accessibility are identified mainly reactively, whereas more developed organisations use standardised procedures for data preparation, fitness assessment, documentation, and continuous monitoring of data quality (UNESCO, 2025, pp. 47–48). This supports the conclusion of the present study that the comparatively stronger state of the technological and information foundations does not automatically convert into readiness for systematic AI implementation. The significance of accumulated prior capacity can also be considered through the concept of absorptive capacity. Cohen and Levinthal define absorptive capacity as the ability to ‘recognize the value of new, external information, assimilate it, and apply it to commercial ends’ and explain that this capacity depends substantially on prior related knowledge (Cohen & Levinthal, 1990, p. 128). In the context of AI, this means that existing capabilities in data management, digitalisation, and analysis may facilitate the subsequent adoption of new applications, but do not guarantee it in themselves.

I.3 Management of projects involving the use and implementation of AI



Figure 7. Management of projects related to the use and implementation of artificial intelligence

Positive ratings increase across all three indicators in 2026. Their share rises from 12.9% to 14.5% for formal approval, from 12.1% to 13.7% for clear allocation of roles and responsibilities, and from 11.8% to 13.0% for monitoring and oversight. Despite the reported improvement, positive ratings remain within the 13–15% range, providing no basis for concluding that these mechanisms are widely established across administrative structures.

The OECD comparative analysis shows that a substantial proportion of AI initiatives in the public sector remain at the exploration, development or pilot stage, with the transition to sustainable use being hindered by insufficiently developed mechanisms for governance, documentation, monitoring, and evaluation (OECD, 2025, pp. 10, 82–85). In this context, the Bulgarian results underscore the need for management capacity to develop in parallel with the expansion of practical AI use.

Negative ratings range from 21.2% to 23.4%, while neutral responses remain predominant, at between 63.3% and 64.4%. The high share of neutral ratings may

indicate that mechanisms for approval, allocation of responsibilities, and control are not sufficiently visible or recognisable to employees. The results point to limited improvement, but do not provide convincing evidence of a consistently developed system for managing AI projects. This also matters for the organisation's ability to derive knowledge from individual initiatives. If decisions on approval, monitoring, and evaluation remain informal, the results of one project are more difficult to use in subsequent applications. Organisational learning requires accumulated experience to be progressively incorporated into established systems, structures, and procedures so that knowledge does not remain confined to a particular team or project (Crossan, Lane & White, 1999, p. 529).

I.4 Organizational culture and outcomes

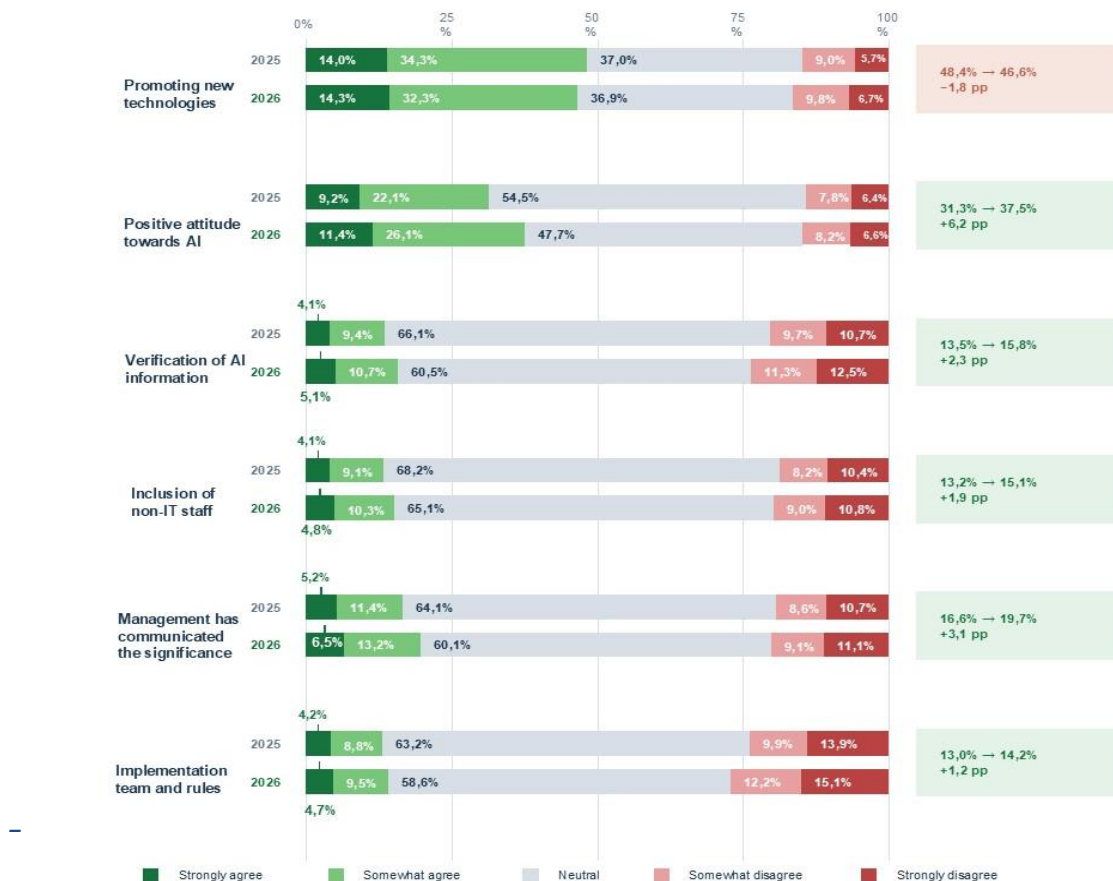


Figure 8. Organizational culture and outcomes

The results indicate a limited but consistent improvement in the organisational environment relating to AI, with five of the six indicators increasing. The strongest growth is in positive attitudes towards AI, rising from 31.3% to 37.5% (+6.2 percentage points). Comparison with the other indicators shows that attitudes towards AI are changing faster than the specific organisational mechanisms for its implementation.

Encouragement of the use of new technologies is the only one of the six indicators in the pillar to decline, from 48.4% to 46.6% (-1.8 percentage points). The decrease is limited,

and the indicator remains the highest in the group. The data do not allow the reasons for the change to be established, but they show that general support for new technologies is not moving in the same direction as the more specific attitudes and practices relating to AI.

Practical organisational mechanisms remain less developed. The highest value among them is recorded for management communication, which rises from 16.6% to 19.7% (+3.1 percentage points). Verification of AI-generated information, the involvement of employees outside IT units, and the existence of an implementation team and rules remain within the 14.2–15.8% range. The positive shift in attitudes towards AI has therefore not yet been accompanied by comparable development of the mechanisms needed to turn it into sustainable organisational practice.

This distinction is consistent with research on learning organisations, which emphasises three interrelated conditions: a supportive learning environment, concrete learning processes and practices, and leadership that actively reinforces these processes (Garvin, Edmondson & Gino, 2008, p. 2). In this respect, a positive attitude towards AI is a favourable precondition, but sustainable organisational learning also requires opportunities to discuss problems, exchange experience, experiment, and apply lessons learned in subsequent decisions.

I.1 Readiness for the Artificial Intelligence Act

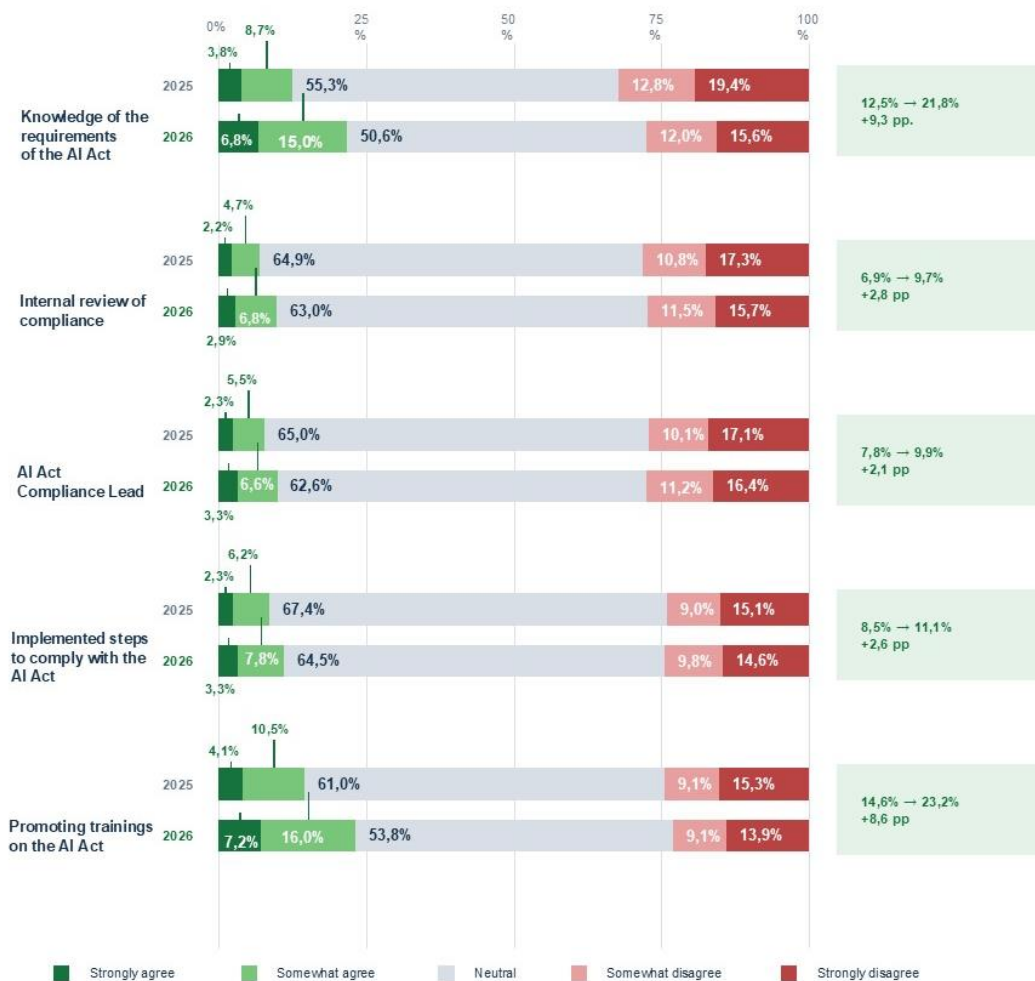


Figure 9. Readiness for the Artificial Intelligence Act

This pillar contains the two largest increases within the organisational component. The share of positive ratings regarding knowledge of the requirements of the AI Act rises from 12.5% to 21.8% (+9.3 percentage points), while positive ratings of encouragement to undertake training on the Act rise from 14.6% to 23.2% (+8.6 percentage points). The results indicate a marked increase in awareness and in attention to the need for preparation.

However, the gap between awareness and action taken indicates that regulatory readiness is still developing primarily at the level of familiarity with the requirements. More mature institutional readiness requires these requirements to be embedded in ongoing management processes.

In this respect, the OECD approach to responsible AI governance treats risk management as a sequential cycle: embedding responsibility in policies and management systems; identifying and assessing potential adverse impacts; taking measures to prevent and mitigate risk; tracking results; and communicating the actions taken (OECD, 2026a, pp. 6,

18–19). Although this framework was developed for responsible business conduct, its governance logic is also relevant to the distinction between formal awareness of regulatory requirements and their incorporation into actual organisational processes.

From this perspective, designating responsible persons, conducting an internal review of the Act's applicability and taking specific compliance measures should not be isolated administrative actions. Together, they will indicate whether the institution is beginning to build a sustainable mechanism for managing regulatory and ethical risks associated with AI use.

However, the indicators relating to specific organisational actions remain substantially lower. Positive ratings of a conducted internal review of applicability are reported by 9.7% of respondents; 9.9% report a designated responsible person; and 11.1% report steps taken towards compliance. Therefore, awareness and support for training reach approximately 22–23%, while specific actions remain around 10–11%. This gap points to an early stage of preparation in which recognition of the importance of regulation is growing faster than the introduction of internal reviews, assigned responsibilities, and specific measures.

The legal significance of these results depends on the type of AI system used, its risk category, and the role of the administration concerned. Not every AI application gives rise to the same obligations. The requirement to take measures to support AI literacy applies to providers and deployers of AI systems. Additional requirements on risk management and human oversight, as well as obligations related to use, apply primarily to high-risk systems.

Bodies governed by public law must also carry out a fundamental rights impact assessment before the first use of certain high-risk systems. The obligations apply in stages and do not cover all uses of AI in public administration in the same way (Regulation (EU) 2024/1689, Articles 4, 9, 14, 26 and 27, as amended by Regulation (EU) 2026/1744).

The observed gap between awareness and specific action nevertheless indicates that the mechanisms for determining the applicable requirements, assigning responsibilities and preparing for their implementation are still not sufficiently visible to a large proportion of respondents. In this respect, the OECD emphasises that accountability requirements are particularly high when AI is used by public authorities because of its potential impact on rights, administrative services, and public trust. The main groups of risks include ethical and operational risks, the risk of exclusion, public resistance, and the risk of inaction (OECD, 2025, pp. 33–35). From this perspective, organisational readiness requires not only familiarity with the legal requirements, but also the capacity to identify risks, assign responsibilities, and monitor the effects of AI use.

The UNESCO framework shows how these principles can be translated into organisational practice. Ethical considerations should be incorporated into standard review procedures

through assessment of potential bias, explainability, and the ethical impact of systems (UNESCO, 2025, p. 41). Documented compliance processes are also required, combining technical, legal, ethical, and governance expertise with existing mechanisms for legal oversight (UNESCO, 2025, p. 43).

This is the only organisational pillar in which the average level of disagreement decreases. For the indicators concerning knowledge of the Act and encouragement of training, the increase in positive ratings is accompanied both by a contraction in neutral responses and a decline in negative responses. This indicates a clearer positive shift, but for the time being primarily at the level of awareness and training rather than specific organisational action.

I.2 Current level of AI use

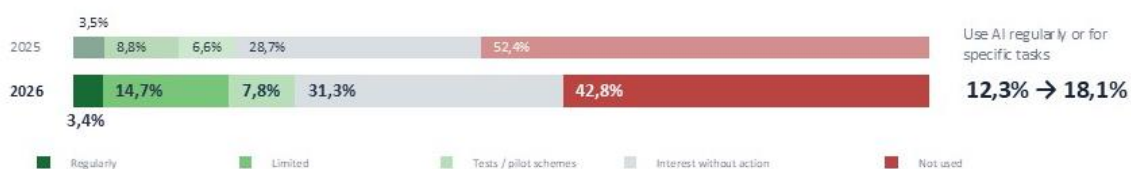


Figure 10. Current level of artificial intelligence use

The share of respondents indicating that AI is used on a regular basis or to a limited extent in specific activities in their administration rises from 12.3% in 2025 to 18.1% in 2026 (+5.8 percentage points). At the same time, the share of responses stating that AI is not used falls from 52.4% to 42.8%, a decrease of 9.6 percentage points. This is the largest change in any single category among the comparable indicators included in this section.

However, the increase is not driven by growth in regular use. Its share remains virtually unchanged: 3.5% in 2025 and 3.4% in 2026. The increase is concentrated in the category 'limited use in specific activities', which rises from 8.8% to 14.7% (+5.9 percentage points). AI use is therefore expanding primarily through individual applications rather than a shift towards regular and integrated use. More respondents report using AI for specific tasks, while the share describing it as a regular practice remains unchanged. Therefore, the overall figure of 18.1% should not be interpreted as evidence that a higher level of organisational maturity has been reached. It mostly reflects the expansion of AI into a limited range of activities.

The distinction between limited use and more sustainable organisational implementation can also be considered through the classic tension between exploration of new possibilities and exploitation of established solutions. The former involves search, experimentation and discovery, while the latter involves refinement, execution and increasing the efficiency of established practices (March, 1991, pp. 71, 85). The 2026 data indicate an expansion of early-stage experimentation with AI in specific tasks, while the transition to regular use remains limited.

Together with the 42.8% of responses that AI is not used, this means that 74.1% of respondents are not reporting current institutional AI use. At the same time, the share reporting interest without action is increasing, indicating potential for subsequent development, but not an already established practice.

1.6.1 Analysis of responses to the open-ended question on sharing real-world examples

In the question on current AI use, respondents were also given the option of providing a specific example from their work. A total of 653 people responded, representing 11.9% of the 5,475 participants. Because the question was voluntary, these responses do not constitute a representative subsample and cannot be generalised to all respondents. They provide additional qualitative information on the nature of the applications, initiatives, and constraints described.

The responses include not only examples of current use, but also possible or desired applications, test and pilot initiatives, and identified barriers. Their analysis complements the results of the closed-ended questions by showing that respondents identify considerably more potential uses for AI than what they are applying in their work.

The following categories were used for the content analysis:

- Actual use – a specific work activity or application is described in which AI is being used.
- Identified or desired application – a possible use of AI is described, without clear evidence of current implementation.
- Test or pilot application – an experiment, pilot initiative, development activity or ongoing implementation is described.
- Reason or barrier – constraints are identified, such as lack of access, rules, resources or institutional permission.
- Other responses – there is a lack of sufficiently specific information to assign the response to one of the other categories.

The ‘Actual use’ category shows that, among the subgroup who responded, there is a limited but clearly identifiable set of practical applications. These are concentrated primarily in text- and information-related tasks: preparing and editing documents, searching for and summarising information, translation, and creating publications and presentations. In the examples described, AI generally performs a supporting function and does not independently participate in administrative decision-making.

This picture is consistent with the results in Chapter 2, according to which general-purpose language models are used by 40.4% of respondents, while specialised tools and AI agents are considerably less widespread, at 3.2% and 1.4% respectively. Taken together, the findings indicate that at this stage AI is used primarily as an assistive tool for the individual employee rather than as an integrated capability that transforms an administrative process or service delivery.

The prevailing character of actual use is illustrated by the following response:

'At present, it is used to a limited extent as a supporting tool for preparing correspondence that does not require in-depth expertise and does not involve certain specifics.'

The largest share of responses falls within the 'Identified or desired application' category. In these responses, participants identify opportunities to use AI in routine and day-to-day activities, including administrative service delivery, but without clear evidence of current implementation or an adopted institutional decision. The following response is illustrative:

'I have ideas for implementing AI that would be useful to colleagues, as well as a chatbot for the website to assist citizens. Overall, I have many ideas, but no budget to implement them.'

These responses show that recognition of potential applications is more widespread than their practical implementation. They do not constitute ready-made institutional plans; rather, they identify areas in which employees see opportunities for AI use.

The 'Test or pilot application' category accounts for 5.4% of the open-ended responses. This figure is close to the 7.8% reported in the closed-ended question on tests and pilot initiatives. The comparison is descriptive only, since the two percentages are calculated for different groups of respondents and do not measure entirely identical phenomena. Nevertheless, the results indicate the existence of a limited but clearly identifiable set of AI experiments.

Some responses describe initiatives that remain at the stage of technical specification, testing or prototype development, with no information on subsequent implementation. This is illustrated by the following response:

'It is still only used as a test, not in actual processes.'

Attempts to apply AI in administrative service delivery are also reported, but without sufficient information on their results, continuation or scaling:

'An attempt was made to apply AI in the provision of administrative services to citizens by the unit in which I work.'

These examples do not allow the success of the initiatives to be assessed, but they show that some experiments have not yet progressed to established organisational practice.

The 'Reason or barrier' category is small in volume but provides additional information because the constraints were raised spontaneously in response to a question about AI applications. This does not give them greater statistical weight than the results of the closed-ended questions, but it does indicate which problems were sufficiently important for respondents to mention on their own initiative.

The constraints identified include a lack of rules, institution-provided access and resources, as well as reservations about the quality and reliability of AI outputs. The latter

may indicate awareness of the technology's limitations, but the responses do not establish whether this awareness is accompanied by systematic verification of outputs.

The following responses illustrate the gap between individual use and institutional support:

'There is no policy or set of rules; individual employees use AI to make their work easier.'

'AI use is based on personal initiative and the capabilities of individual experts, rather than being the result of institutional policy.'

These responses are consistent with the findings of the Index itself, which show a substantial difference between the use of personal access without institutional approval and access through an institutional licence or a centrally deployed system.

The 'Other Responses' category includes cases in which respondents mention only a tool or method of access, an institutional initiative without a specific application, stated use without an example, training, or general or unclear statements. These responses do not contain sufficient information to establish a specific practical use of AI or to assign them to the other analytical categories.

The quoted responses serve an illustrative purpose and should not be regarded as representative of all participants in the study.

I.3 Would you like to work on practical applications of artificial intelligence?



Figure 11. Desire to work on practical applications of artificial intelligence

The share of respondents who state that they would definitely or probably be willing to work on practical AI applications rises from 44.7% in 2025 to 56.6% in 2026 (+11.9 percentage points). This is one of the most substantial positive increases in the study and indicates a broadening willingness among employees to participate in the practical application of AI.

An experimental study involving 801 public servants in the United Kingdom found that attitudes towards AI become more reserved as its role expands from advisory support to participation in decision-making. At the same time, providing specific information about potential AI applications is associated with more positive attitudes (Haesevoets et al., 2026). Although these findings are not directly comparable with the present study, they underscore the importance of clearly defining the role of AI and the conditions under which it is used.

Comparison of the two IPA Index survey rounds shows both a decline in the share of respondents who are uncertain and a lower share of negative responses. The proportion

answering ‘cannot assess’ falls from 25.3% to 20.4%, the combined share of negative responses from 29.9% to 22.9%, and the share expressing a definite unwillingness to participate from 7.5% to 5.1%.

The increase in positive responses is therefore not only caused by lower uncertainty; it is also accompanied by reduced reservations about practical work with AI. Since the data come from two independent samples, the difference should be interpreted as a change between the two survey rounds rather than as a tracked change among the same employees. Growing willingness is an important precondition for expanding practical applications but converting it into sustainable organisational capacity requires concrete opportunities for participation, training, authorised access, and institutional support.

I.4 Overall, our organisation is ready to implement artificial intelligence

The mean score for the statement ‘Overall, our organisation is ready to implement artificial intelligence’ rises from $\mu = 2.13$ in 2025 to $\mu = 2.41$ in 2026. The share of positive ratings increases from 11.1% to 12.5% (+1.4 percentage points). This represents a positive change in perceived organisational readiness, but the mean remains below the neutral point on the five-point scale. The result indicates limited improvement and does not provide grounds for concluding that organisational readiness has become widespread.

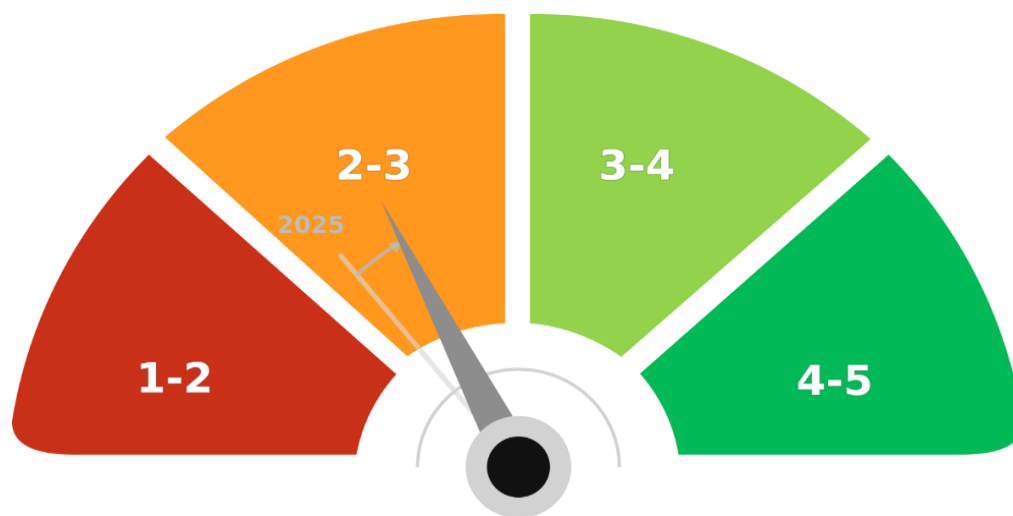


Figure 12. Overall, our organisation is ready to implement artificial intelligence

The different rates of change in practical use and organisational readiness are consistent with the early stages of institutional maturity described by UNESCO. At these stages, processes are often inconsistent, reactive, and heavily dependent on the initiative of individual employees. Progression to the next level requires practices gradually to become documented, repeatable, and supported by common organisational mechanisms (UNESCO, 2025, pp. 7–8).

This allows the results for Bulgaria to be interpreted not simply as organisations lagging behind employees, but as reflecting a transitional phase of institutionalisation. AI is already entering day-to-day work, but some practices have not yet been converted into established rules, shared resources, assigned responsibilities, and repeatable organisational processes.

II. Individual capacity

**KNOWLEDGE AND SKILLS OF
PUBLIC ADMINISTRATION
EMPLOYEES IN THE
APPLICATION OF ARTIFICIAL
INTELLIGENCE**



In 2026, the knowledge and skills indicators are divided into two groups: practical skills for working with AI and skills for managing and organising its implementation. The first group measures employees' self-assessed ability to use AI for specific tasks. The second covers knowledge and skills in identifying suitable applications, organising projects, managing risks, and ensuring responsible use.

This distinction reflects the difference between individual use of a tool and participation in its organised institutional implementation. Practical skills enable employees to apply AI in their day-to-day work, whereas management skills support the incorporation of individual applications into more sustainable organisational processes. However, just the possession of such skills is insufficient. Institutional rules, resources, assigned responsibilities, and mechanisms for sharing accumulated experience are also required.

This distinction is consistent with the literature on organisational learning. An organisation's ability to recognise the value of new knowledge, absorb it and apply it depends on its accumulated prior capacity and cannot be reduced to the simple sum of employees' individual competences (Cohen & Levinthal, 1990, p. 128). Individual knowledge acquires organisational significance when it is shared, aligned, and gradually embedded in common structures, procedures, and practices (Crossan, Lane & White, 1999, pp. 525, 529). Growth in knowledge and skills is therefore necessary but is not in itself sufficient evidence of increased organisational capacity.

1. PRACTICAL KNOWLEDGE FOR WORK WITH AI TOOLS

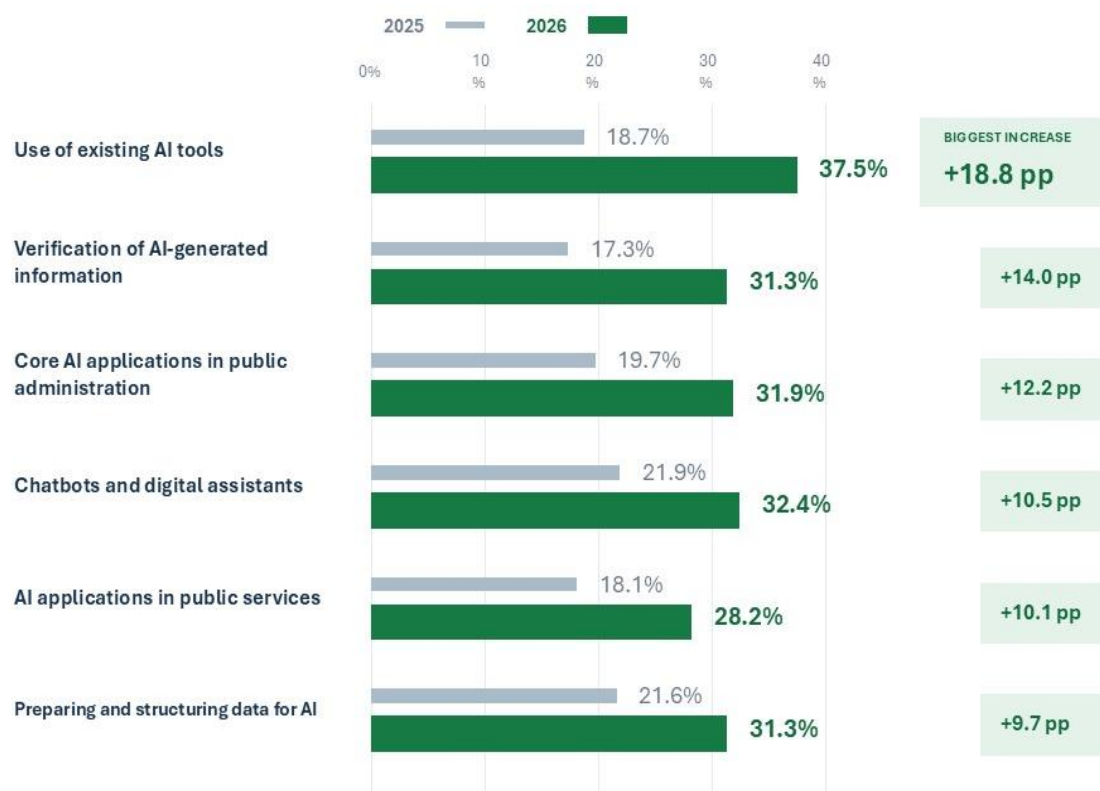


Figure 13. Knowledge of practical work with AI tools

In 2026, positive ratings increase across all six indicators relating to practical work with AI. The largest increase is in the use of existing AI tools (+18.8 percentage points), followed by verification of the reliability of generated information (+14.0 percentage points). Across the remaining four indicators, the increase ranges from 9.7 to 12.2 percentage points. This is the group of indicators showing the most rapid change in the study and indicates a substantial increase in self-assessed practical capacity.

The leading indicator in the group also changes. In 2025, the highest share was recorded for the use of digital assistants (21.9%), whereas in 2026 the use of existing AI tools ranks first (37.5%). The results indicate that practical knowledge is no longer uniformly low and more substantial experience is accumulating in certain areas. Since the data come from two independent samples, this does not demonstrate that the same employees have progressed towards more advanced use; rather, it indicates a change in the overall profile of self-assessed capacity.

Particular attention should be paid to verification of the reliability of AI-generated information. At 31.3%, an increase of 14.0 percentage points, it is among the highest-rated individual skills. At the same time, only 15.8% of respondents give a positive rating of the existence of an organisational practice for checking AI outputs. The two indicators measure different phenomena and are not directly comparable, but a descriptive comparison shows that individual employees' confidence in their own skills is substantially more widespread than visible institutional verification procedures.

Positive ratings increase across all six indicators. The largest rise is in knowledge of ethical and responsible AI use (+14.0 percentage points), while the smallest is in AI project management (+6.5 percentage points). The latter result is consistent with the organisational bottleneck where mechanisms for approval, allocation of responsibilities, monitoring, and oversight also remain underdeveloped.

Despite the overall improvement, three of the six indicators remain below 25%: AI project management (17.3%), knowledge of the requirements of the AI Act (18.9%), and identification of suitable applications (21.9%). These are areas directly relevant to the transition from individual use of tools to organised and responsible institutional implementation.

Development is uneven, and the overall rise in self-assessed capacity is accompanied by substantial differences between its individual components.

Comparison with practical skills shows that the ability to use existing tools is developing faster than the knowledge required to organise and manage implementation and to ensure compliance with applicable requirements. This finding is consistent with the overall pattern in the study: practical use of AI is expanding faster than the capacity for its systematic direction and institutional support. Since both groups of indicators are based on self-assessments, the results measure the perceived possession of knowledge and skills rather than the actual quality of management and implementation.

The data illustrate that the growth of AI competences is uneven. Employees are developing the ability to use available tools more quickly than the knowledge required for their organisational implementation, management, and control. This distinction is also important in the OECD's approach to public administration capacity. Building AI readiness cannot be reduced to basic literacy or the ability to work with a particular tool. Different competences are required for different roles in public administration, including the ability to assess applications, manage risks, commission and procure AI solutions, work with data, carry out legal and ethical assessments, and participate in multidisciplinary teams (OECD, 2025).

On this basis, the next stage in developing human capacity calls not simply for more training, but for differentiation of competences. General AI literacy should be complemented by specialised profiles for managers, policy experts, lawyers, data and information-technology specialists, public procurement officers, and experts involved in the management of specific AI applications.

3. ANALYSIS BY AGE

The analysis identifies a clear and consistent association between age and the self-assessed level of knowledge and skills for working with AI. For each respondent, the number of areas in which they report an intermediate or advanced level was calculated. The mean is 5.1 out of 12 areas among employees up to age 35, 3.5 in the group aged 35–50, and 2.9 among those over 50. No intermediate or advanced level in any of the areas examined is reported by 28.5% of respondents up to age 35, 42.8% of those aged 35–50, and 49.6% of employees over 50 (Table 1).

Age group	Number of respondents	Average number of areas at an intermediate or advanced level (out of 12)	No intermediate or advanced level in any area
Up to 35 years	621	5.1	28.5%
Aged between 35 and 50	2,596	3.5	42.8%
Over 50	2,258	2.9	49.6%

Table 1. Self-assessed knowledge and skills for working with AI by age group

Note: For each respondent, the number of areas in which an intermediate or advanced level was reported was calculated. A value of zero does not mean a complete absence of knowledge; it means that a basic level or no knowledge was reported in every area

The observed differences should not be interpreted as fixed characteristics of individual age groups. They indicate differences in knowledge and practical experience of working with AI, implying different needs for training and support. In the UNESCO framework, AI literacy and the management of organisational change are treated as separate elements of organisational maturity. This underscores the role of the institution in creating conditions in which employees can develop the ability to understand, use and critically assess AI, rather than leaving the development of these competences primarily to individual initiative (UNESCO, 2025, pp. 20–25).

The findings of the present study show that a uniform training approach may not be sufficient where substantial differences in knowledge and practical experience exist between groups of employees. This points to the need for differentiated forms of training tailored to employees' level of preparedness and the nature of the functions they perform.

The largest differences concern practical work with existing AI tools. An intermediate or advanced level is reported by 58.1% of employees up to age 35, 39.5% of those aged 35–50, and 29.5% of employees over 50. A consistent decline with age is also observed in knowledge of the main applications of AI, verification of generated information, work with chatbots and digital assistants, recognition of bias, and data preparation (Table 2).

Selected skills	Up to 35 years	35–50 years	Over 50	Difference between the under-35 and over-50 age groups
Working with existing AI tools	58.1%	39.5%	29.5%	+28.6%
Main applications of AI	48.8%	32.7%	26.2%	+22.6%
Verification of generated information	48.1%	31.7%	26.1%	+22.0%
Chatbots and digital assistants	47.8%	33.1%	27.3%	+20.5%
Recognising bias	43.6%	27.3%	24.2%	+19.4%
Data preparation	43.3%	32.0%	27.2%	+16.1%
Management of AI projects	26.7%	17.7%	14.1%	+12.6%

Knowledge of the Artificial Intelligence Act	25.3%	18.8%	17.2%	+8.1%
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Table 2 Selected skills at intermediate or advanced level by age group

The differences are smaller for knowledge of the AI Act and AI project management. This does not mean that preparedness is similarly high. Levels are low across all age groups, indicating a general shortage of regulatory and managerial knowledge rather than a difficulty confined to a particular age group.

Individual skills by age group

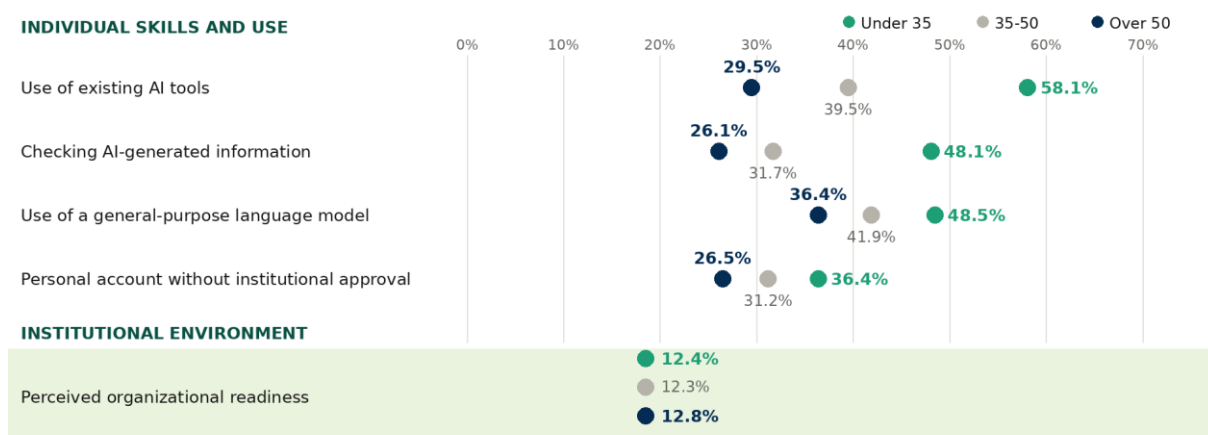


Figure 14. Self-assessed knowledge and skills in working with AI by age group

The association between age and self-assessed skills remains after statistically adjusting for sex and position. For work with existing AI tools, employees up to age 35 have 3.38 times the odds of reporting an intermediate or advanced level compared with employees over 50 (OR = 3.38; 95% confidence interval: 2.80–4.07; $p < 0.001$). Therefore, the observed association cannot be explained only by differences in sex and position between the age groups.

Differences in self-assessed skills are also reflected in practical use. General-purpose language models are used by 48.5% of employees up to age 35, 41.9% of those aged 35–50, and 36.4% of employees over 50. AI is used actively or occasionally for generating ideas by 39.5%, 32.2%, and 25.2%, respectively. A personal account without institutional approval is used by 36.4% of the youngest group and 26.5% of employees over 50. Higher self-assessed skills among younger employees are therefore accompanied by more active practical use.

Greater use is not associated with lower sensitivity to risk. Employees up to age 35 more often identify lack of access, concerns about data security, distrust of outputs, and the absence of clear internal rules. Among respondents who use at least one type of AI tool, the differences persist regarding access, security, and the reliability of outputs. This indicates that a critical attitude should not necessarily be interpreted as resistance. Greater practical exposure probably makes the technology's limitations and risks more visible.

Unlike individual skills and practical use, assessments of the institutional environment differ very little by age. High or very high organisational readiness, corresponding to scores of 4 or 5 on the five-point scale, is reported by 12.4% of employees up to age 35, 12.3% of those aged 35–50, and 12.8% of employees over 50. The differences are not statistically significant ($p = 0.862$). Systematic knowledge sharing is reported by between 3.4% and 4.3% of respondents in each group, again with no statistically significant difference ($p = 0.481$). Younger employees therefore enter practical AI use more actively, but operate under similar constraints in terms of access, internal rules, organisational support, and knowledge exchange.

Comparison with 2025 shows higher shares in both age groups being compared, but no convergence between them. For practical work with AI tools, the share of employees reporting an intermediate or advanced level rises approximately from 25% to 58.1% among employees up to age 35 and from 17% to 34.9% among those over 35. Since the two studies cover different samples, the results indicate change at the level of the age groups rather than individual development among the same respondents.

The results reflect self-assessed knowledge, skills, and practices rather than objectively measured performance. Therefore, they do not demonstrate that age in itself determines the ability to work with AI. The observed differences may also be related to access to tools, prior experience, and frequency of use. However, their consistency indicates a need for practical learning opportunities adapted to employees' different starting levels.

Overall, age is clearly associated with the level of self-assessed skills and practical AI use, whereas assessments of the institutional environment differ very little by age. Younger employees use the technology more actively and more often identify the associated constraints and risks. This advantage, however, remains predominantly individual when the organisation does not provide shared tools, rules and learning mechanisms.



CHAPTER 2

INSTITUTIONAL LEARNING AND PRACTICES

WHEN USING ARTIFICIAL
INTELLIGENCE

The expanding use of AI raises a question that goes beyond individual uptake of new tools: to what extent is public administration capable of learning from accumulated experience? The concept of the learning organisation provides an appropriate framework for examining this process. It directs attention to an organisation's ability to continually expand its capacity for action through systems thinking, shared vision, and team learning (Senge, 1990, pp. 10, 14).

This distinction is particularly important in the case of AI. Individual employees may adopt new tools relatively quickly, whereas changes to organisational rules, processes, and responsibilities take more time. Individual learning acquires institutional significance when accumulated knowledge is interpreted collectively, integrated into shared practices, and gradually embedded in the organisation's systems and procedures (Crossan, Lane & White, 1999, pp. 525, 529). Therefore, this chapter examines not only whether employees use and experiment with AI, but also whether individual experience is beginning to develop into shared organisational knowledge and sustainable institutional practice.

A 2021 systematic review of the international literature on AI and public governance notes that research in this specific field was still at an early stage of theoretical development: only a small proportion of the studies reviewed at the time applied, tested or developed theory (Zuiderwijk, Chen & Salem, 2021, p. 16). In view of this scarcity of AI-specific theory, the present chapter examines institutional learning through the lens of established concepts of organisational learning (Senge, 1990; Crossan, Lane & White, 1999).

1. Main barriers to the use of AI

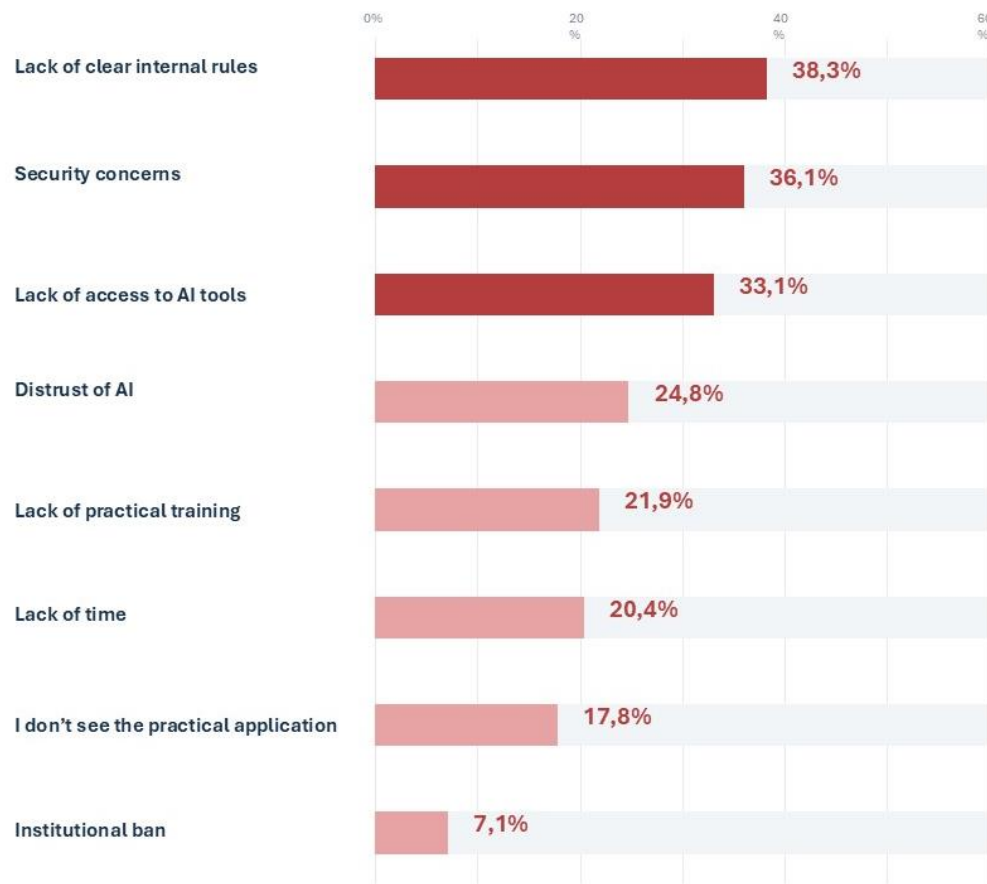


Figure 15. Key barriers to the use of artificial intelligence

The barriers identified relate primarily to organisational conditions and the governance of AI use. Respondents most frequently cite the absence of clear internal rules (38.3%), security concerns (36.1%), and lack of access to suitable AI tools (33.1%). Distrust of AI is reported by 24.8%, and the absence of a clearly identifiable application in their work by 17.8%. Only 7.1% report an explicit institutional ban.

The results indicate that the principal constraint is not a categorical rejection of AI use, but the absence of sufficiently clear and secure conditions for its application. Rules, access, and security emerge as interrelated factors, while the lack of authorised tools and clear guidance makes it difficult for employees to determine when, for what purposes and with what data they may use AI.

A similar picture emerges from the European Commission Joint Research Centre's analysis of generative AI in the European public sector. It identifies interconnected challenges relating to human oversight, accountability, data protection, governance, safety, fairness, and transparency (Brizuela et al., 2025). These issues should therefore be treated as elements of an overarching organisational framework for responsible AI use, rather than as standalone requirements that can be addressed in isolation.

2. AI tools used

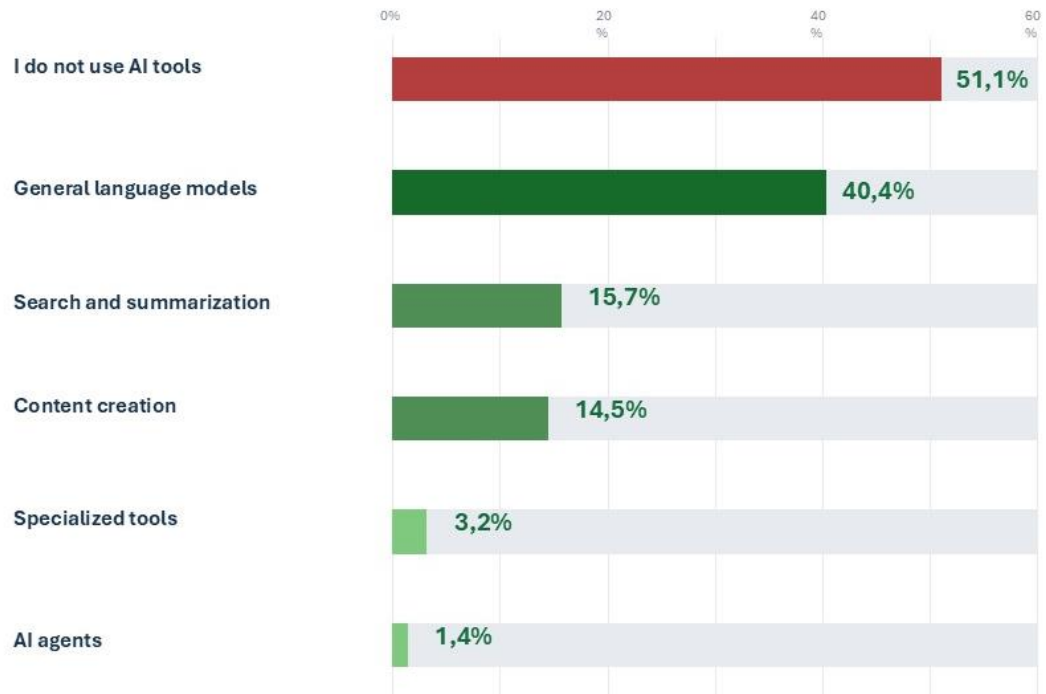


Figure 16. Most commonly used AI tools

Just over half of respondents (51.1%) report that they do not use AI tools. Among the categories specifically identified, general-purpose language models are the most widespread (40.4%), followed by tools for searching and summarising information (15.7%) and for content creation (14.5%). Specialised tools and AI agents remain uncommon, at 3.2% and 1.4%, respectively.

The results indicate that use is concentrated primarily in general-purpose tools capable of supporting a wide range of text-based and information-related tasks. The use of specialised solutions designed for specific administrative functions or integrated workflows is considerably more limited. At this stage, AI is used mainly as an assistive tool for individual tasks rather than as a permanently embedded capability that transforms an administrative process or service.

Comparison with the access data adds important governance context. While 51.1% report no use of a specific AI tool, 46.8% state that they do not have access. The two questions measure different phenomena, and the difference between these values does not in itself establish how many employees have access but do not use AI, or how many use tools outside an institution-provided channel. Such a conclusion would require analysis of the combination of responses at the individual level.

Nevertheless, the overall picture shows both widespread use of general-purpose language models and limited institution-provided access. This supports the conclusion that

practical AI use is developing faster than the organisational mechanisms for providing, guiding, and controlling it.

3. Types of access to AI tools

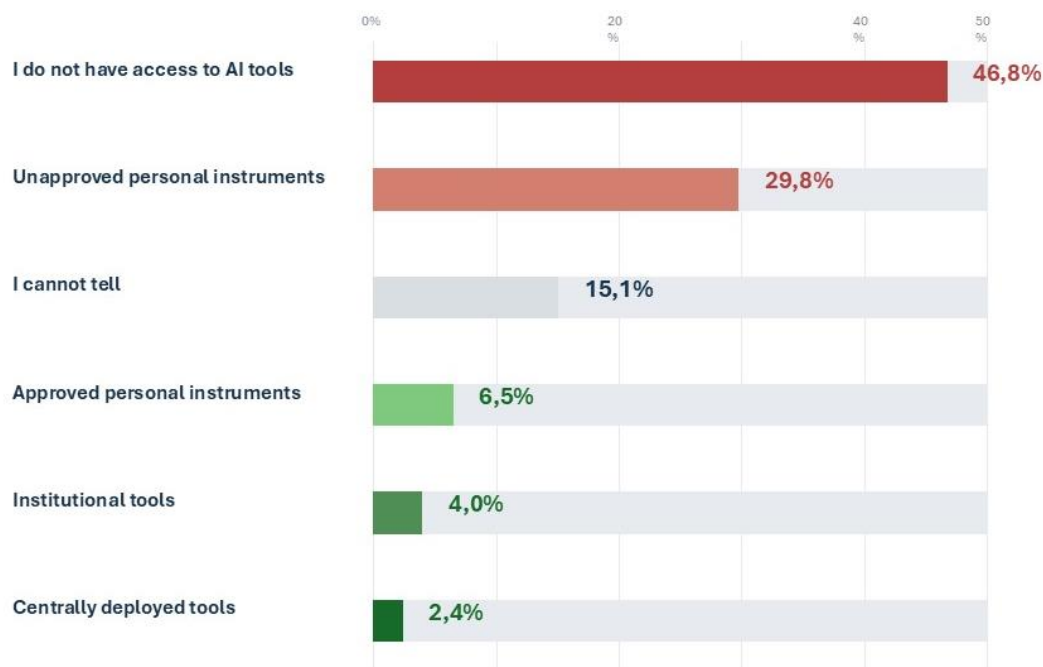


Figure 17. Types of access to AI tools

Almost half of respondents (46.8%) state that they do not have access to AI tools. At the same time, 29.8% report using a personal account without institutional approval, while 6.5% report using a personal account with their institution's permission. Institution-provided forms of access remain considerably less widespread: 4.0% use an institutional licence and 2.4% a centrally deployed system. The pattern observed in the Index is not specific to Bulgaria. Mikalef et al. (2026, p. 21) find that, in the absence of formal organisational solutions, employees may turn to personal accounts and informal use of external generative AI tools.

The question allows more than one response, so the shares for individual modes of access may overlap and should not be added mechanically. Among respondents who report using AI, 92.8% selected only one mode of access and 7.2% more than one. This indicates that hybrid models combining personal and institution-provided channels are still relatively uncommon.

The results outline a bottom-up pattern of AI adoption in which employees' personal initiative develops more rapidly than institution-provided access. Individual adaptation to the technology is outpacing the introduction of common rules, official tools, and governance mechanisms. This does not demonstrate unlawful use in every individual case, but it indicates the potential existence of a governance gap in which practice expands before sufficiently clear and visible institutional conditions have been established.

The use of personal accounts without institutional approval creates conditions for so-called ‘shadow AI’. In such cases, work-related content may be entered into external services without prior risk assessment, approved rules for handling data, or documented control procedures. The data do not establish whether this actually occurs in every specific case, but they do indicate a substantial extent of access outside officially provided institutional channels.

The 15.1% of respondents who are unable to determine the status of the access they use also merits attention. This result does not demonstrate the absence of an internal policy, but it may indicate that the rules and permitted modes of AI use have not been defined or communicated to employees with sufficient clarity. From a governance perspective, uncertainty about permitted access constitutes a separate risk because it makes it more difficult to distinguish between authorised use, unauthorised use, and use not covered by internal rules.

Multiple responses identify a small group using a hybrid model in which personal accounts are combined with institutional licences, officially permitted use or centrally deployed systems. These combinations may reflect the use of different tools for different tasks or a transition towards more formalised access. The combination of ‘personal account without approval’ and ‘personal account with institutional permission’, reported by only 64 respondents, should be interpreted cautiously. It may refer to different tools and situations, but it may also indicate an unclear distinction between authorised and unauthorised use.

Taken together, the results show that personal initiative is an important source of experimentation and practical experience but is still rarely supported by an institutional framework. The principal risk does not arise from employees’ initiative itself, but from the expansion of use in the absence of clearly permitted applications, secure official access, rules for handling data, and procedures for verifying outputs. Where such conditions are absent, the practice does not disappear; instead, it remains less visible and more difficult to govern.

The OECD urges governments to consider how AI could support the redesign of processes and systems, rather than merely fitting it into existing structures. It warns: ‘Otherwise, governments run the risk of simply automating inefficiency and further reinforcing misaligned incentives and governance approaches’ (OECD, 2025, p. 107). The appropriate governance response is therefore not a blanket ban, but to bring AI use into an authorised, visible and secure institutional environment. This requires officially provided tools, clearly defined permitted use cases, rules for data, and mechanisms for monitoring and accountability.

The OECD Due Diligence Guidance for Responsible AI provides practical guidance for establishing such a framework. Although the guidance is aimed primarily at enterprises, its recommendations can also inform discussion of organisational AI governance in public administration. It recommends assigning oversight responsibilities to senior management, documenting roles, responsibilities and lines of communication, and

adapting information and record-keeping systems to the management of AI-related risks (OECD, 2026a, p. 21). It also recommends maintaining an up-to-date inventory of AI systems associated with the organisation as a basis for identifying and assessing risks (OECD, 2026a, p. 24).

The high share of use through personal accounts should not be viewed solely as a characteristic of individual employee behaviour. It is also an indicator of a mismatch between demand for practical access to AI and the institutional capacity to provide and govern that access.

The OECD places the effective use of AI in government within a system of mutually reinforcing enablers and safeguards. Alongside skills and data, these include clear roles and responsibilities, coordination, conditions for controlled experimentation, risk management, transparency, and accountability (OECD, 2025). In the absence of these mechanisms, individual experimentation may outpace the organisation's capacity to determine which tools, data and purposes of use are permissible.

From this perspective, the task for institutions is not merely to restrict informal use, but to establish a realistic and secure institutional channel for using AI. This includes appropriate access to tools, comprehensible rules, and a clear distinction between permitted, restricted, and inappropriate applications.

4. Use of AI to generate ideas and innovative solutions

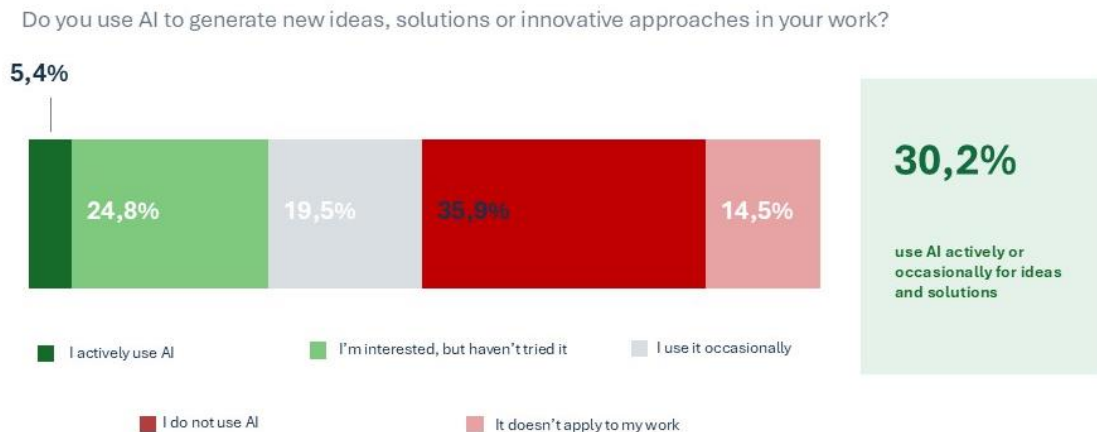


Figure 18. Use of artificial intelligence to generate ideas and innovative solutions

A total of 30.2% of respondents report that they use AI actively or occasionally to generate ideas and solutions. Specifically, 5.4% of all respondents use it actively and 24.8% occasionally. At the same time, 35.9% do not use AI for this purpose, 14.5% state that such activity is not relevant to their work, and 19.5% are interested but have not yet used AI in this way.

The results show that AI is already being used as a tool to support ideation, but for most users this remains an occasional rather than a systematic practice. The substantial

difference between active use (5.4%) and occasional use (24.8%) indicates that AI has entered this area more broadly than it has become a sustained part of working practices.

The 19.5% of respondents who express an interest but have not yet used AI for this purpose also merit attention. This group indicates potential for broader practical use. Moving from interest to actual application, however, requires appropriate access, clear practical guidance, and specific examples of tasks in which AI can be used effectively and responsibly.

The use of AI for idea generation can be viewed as part of an organisation's broader capacity to explore new possibilities. In organisational learning theory, such search, experimentation, and discovery are distinguished from exploiting and refining established practices. The challenge for public administration is to maintain a balance between the two: to create space for exploring new solutions without allowing experimentation to remain disconnected from subsequent evaluation and institutional implementation.

5. Institutional knowledge sharing

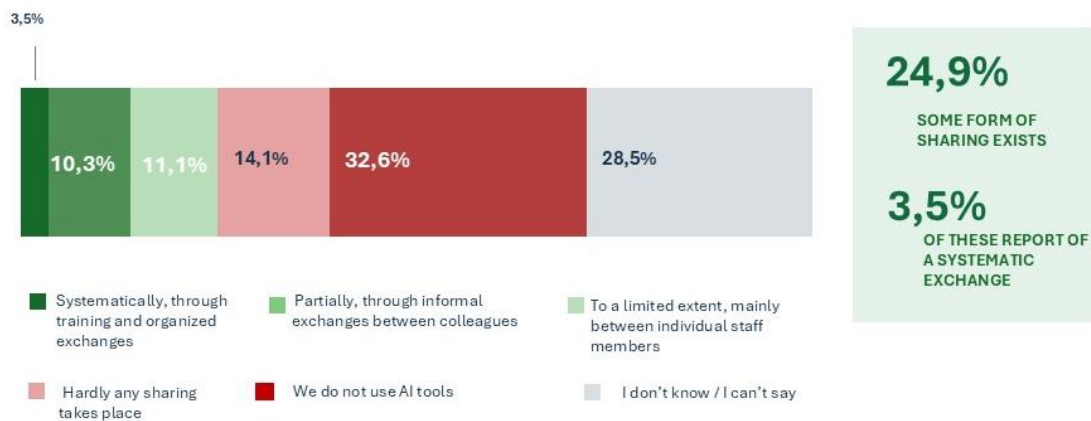


Figure 19. Institutional knowledge sharing in the field of artificial intelligence

A total of 24.9% of respondents report that some form of sharing of AI-related knowledge and good practices exists. Only 3.5%, however, report systematic exchange through training or other organised formats. For 10.3%, sharing is partial and informal among colleagues, while for 11.1% it is limited to individual employees. Thus, where knowledge exchange does exist, it is predominantly informal and only weakly institutionalised.

At the same time, 32.6% state that AI tools are not used in their administration, while 28.5% cannot assess whether knowledge and good practices are shared. The high proportion of 'cannot assess' responses does not demonstrate an absence of exchange but may indicate that existing practices are not sufficiently visible or widespread within the organisation.

This result is also significant from the perspective of organisational memory. The specialist literature draws attention to the problem that, because of specialisation and the distribution of knowledge across different units, organisations do not always have a clear

understanding of what they already know. For accumulated experience to have lasting value, it must not only be acquired but also retained in a way that enables it to be retrieved and used subsequently (Huber, 1991, p. 107). From this perspective, the high proportion of respondents who cannot assess whether AI knowledge is shared within their administration may reflect not only the absence of such practices, but also their insufficient visibility within the organisation.

The results point to a substantial constraint on institutional learning. Individual accumulation of experience with AI is evident elsewhere in the study, whereas organised mechanisms for sharing and retaining that experience remain underdeveloped. Informal exchange among colleagues is useful but does not in itself ensure that acquired knowledge will be preserved, made accessible to other employees and units, and used in subsequent decisions.

This distinction lies at the heart of the concept of the learning organisation. Organisational learning is not limited to adapting to immediate change; it also encompasses the organisation's ability to continually expand its own capacity for action and development. Team learning is central because organisational capacity develops through collective learning rather than merely through the accumulation of isolated individual experience (Senge, 1990, pp. 10, 14). In the context of AI, this means that growth in the number of employees with practical experience is important, but not sufficient if what has been learned remains confined to the individual.

The transition from individual to organisational knowledge can also be understood as a sequential process of interpretation, sharing, integration, and gradual embedding of accumulated experience in the organisation's work. It is this embedding that distinguishes organisational learning from the learning of individuals or temporary groups, as knowledge begins to be reflected in systems, structures, procedures, and established organisational practices (Crossan, Lane & White, 1999, pp. 525, 529). From this perspective, the Index data indicate that a substantial part of AI-related learning remains at the level of individual employees and informal exchange and is less readily converted into sustainable organisational practice.

A more stringent understanding of organisational learning also requires accumulated experience to be capable of changing how the organisation understands and organises its own actions. It is not sufficient for an individual employee to adjust their behaviour. Organisational significance arises when identified discrepancies between expected and actual results lead to a re-examination of shared assumptions and established practices (Argyris & Schön, 1996, p. 16). In the context of AI, this means that practical experimentation acquires broader value when what has been learned influences subsequent decisions, internal rules, the choice of tools or the organisation of workflows.

In this context, structured spaces for collective discussion of information, experience, and results are particularly important for public organisations. The literature refers to these as 'learning forums': regular organisational practices within which employees analyse available information and discuss its implications for future action (Moynihan & Landuyt,

2009, p. 1099). In an empirical study of public organisations, work groups operating as such forums emerged as the strongest of the factors examined in relation to organisational learning (p. 1101). At the same time, the formal establishment of mechanisms for exchange is not sufficient in itself, since organisational structure and culture jointly determine whether information will actually be used for learning and improvement (pp. 1102–1103).

This logic is also consistent with current international frameworks for the use of AI in government. The OECD emphasises that, while AI maturity in public administrations remains limited, learning from practical experience is critical to further progress, and that the exchange of knowledge and practical examples between institutions plays an important role in capacity building (OECD, 2025, p. 3). In the context of rapidly developing technologies, this points to the need for institutions not only to apply predefined rules, but also to systematically assess the results of practice and use what has been learned in subsequent decisions.

A similar approach is reflected in UNESCO's maturity framework for public administrations. Alongside skills and AI literacy, the 'People and Culture' pillar includes organisational structure, leadership, change management, and the adoption of new practices (UNESCO, 2025, pp. 20–25). The development of individual competences is therefore only one aspect of readiness. Organisational mechanisms are also needed through which acquired knowledge can be shared, evaluated, and incorporated into practice.

In this context, the low level of systematic knowledge sharing is an important indicator of the state of institutional learning. If what has been learned remains with an individual employee or team, an administration may accumulate individual experience without converting it into organisational knowledge. Systematic exchange, retention of accumulated experience, its collective evaluation and its use in subsequent decisions should therefore be viewed as part of an administration's capacity to develop sustainable capability for the use of AI.

6. Use of AI in direct work with citizens, businesses or users of administrative services

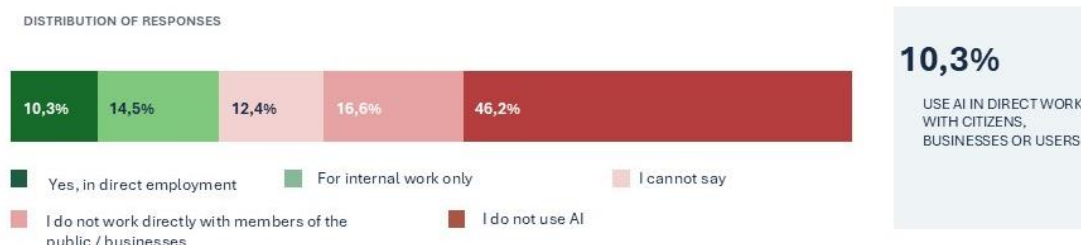


Figure 20. Use of AI tools in direct interaction with citizens, businesses and users of administrative services

The direct use of AI in administrative service delivery remains limited. A total of 10.3% of respondents report using AI in their direct work with citizens, businesses or other users of administrative services. By comparison, 14.5% report using AI only for internal tasks. The data indicate that AI adoption is currently more pronounced in internal work than in direct interaction with service users.

Although the share of direct use is relatively low, this area is particularly sensitive from a governance perspective. In interactions with citizens and businesses, AI-generated content may have an immediate effect on the accuracy, clarity, and quality of the information provided. Even limited use therefore raises questions about verification of outputs, responsibility for the final content, and a clear distinction between AI's assistive function and official administrative information.

The result does not indicate systematic integration of AI into administrative service delivery, but rather early adoption in activities with a direct impact on users. Therefore, its use should be accompanied by clear rules on permitted applications, verification of generated content, and preservation of human responsibility for the outcome. The potential benefits of faster and more accessible communication should be assessed alongside requirements for quality, reliability, and accountability.

7. Use of AI to improve the accessibility of content or communication for people with disabilities

Have you used AI to improve the accessibility of content or communication?

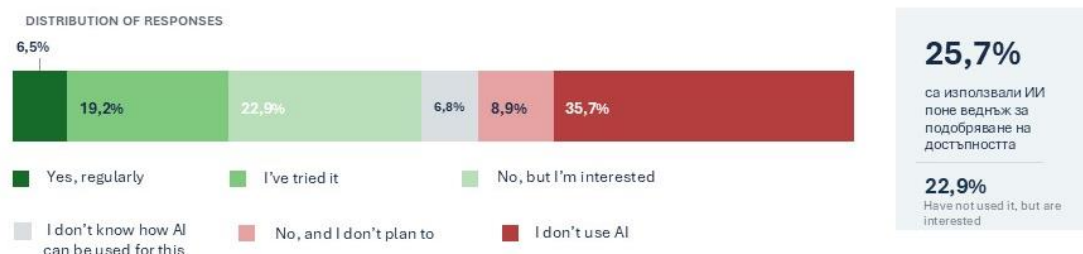


Figure 21. Use of AI to improve the accessibility of content and communication for people with disabilities

A total of 25.7% of respondents report experience using AI to improve the accessibility of content or communication. Specifically, 6.5% of all respondents use it regularly and 19.2% have tried it. A further 22.9% have no such experience yet but express an interest. The distribution shows that experimental use is approximately three times as widespread as regular use. Some practical experience has therefore already been accumulated in this area, but AI use has only rarely become an established practice. At the same time, the share expressing interest is close to that of respondents with practical experience, indicating a substantial reserve of reported willingness for future use.

Accessibility emerges as an area with potential for targeted development because it combines a specific field of application, existing experience, and substantial interest. The data, however, do not show which tools were used, for which specific needs or with what results. Therefore, the reported use should not automatically be taken as evidence of improved accessibility.

From a governance perspective, the next step is not merely to expand use, but to assess its actual outcomes for users. Appropriate tools, practical guidance, and mechanisms are needed to verify whether AI-assisted content becomes more accessible, understandable, and usable for the people for whom it is intended.

8. Encouraging employees to experiment with AI tools

To what extent does your organization encourage staff to experiment with AI tools and learn from practical experience?

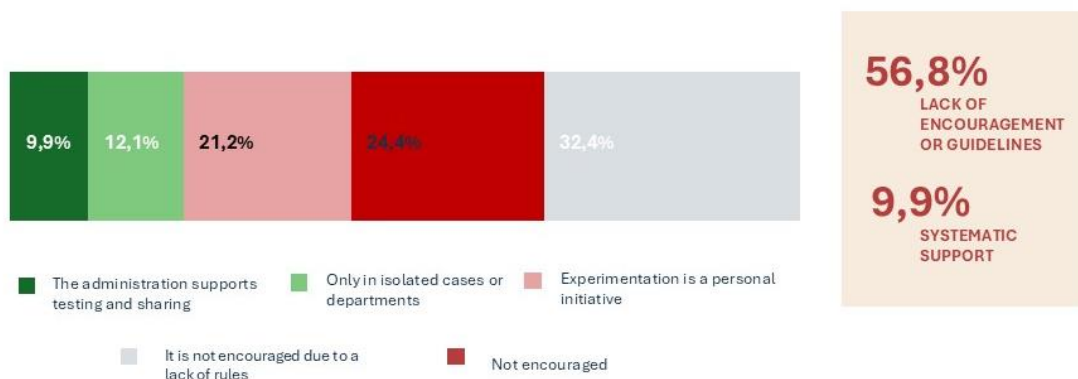


Figure 22. Encouraging staff to experiment with AI tools

The results indicate limited institutional support for experimentation with AI. Only 9.9% of respondents report active support for testing tools and sharing what has been learned. At the same time, 56.8% report a lack of encouragement: 24.4% state that experimentation is not encouraged, while 32.4% associate this with the absence of clear rules. A further 21.2% describe experimentation as a matter of personal initiative.

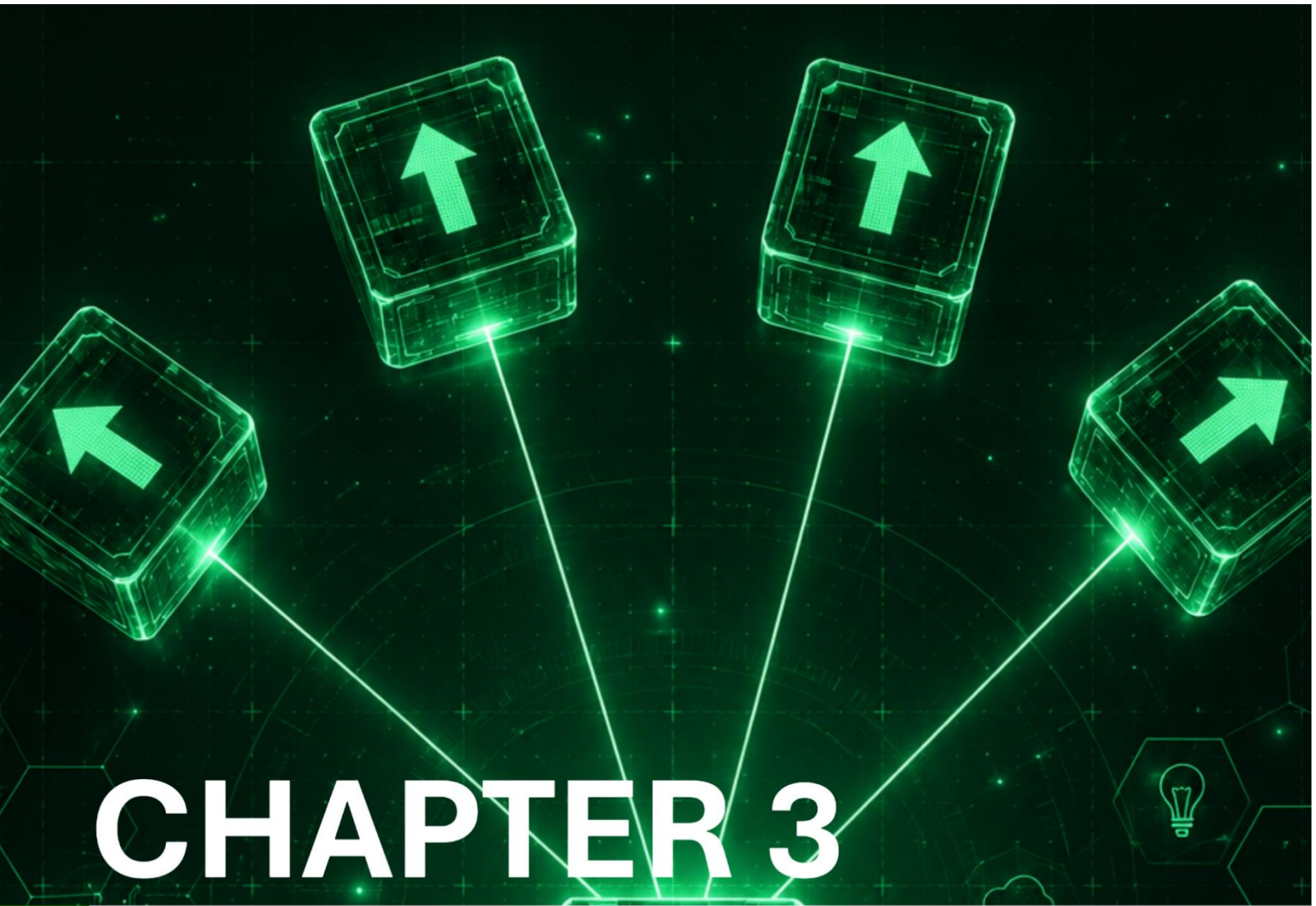
The distinction between these categories is significant. The largest share does not point to an explicit ban or a negative attitude towards AI, but to an absence of rules. This indicates that the principal constraint is uncertainty about the conditions for experimentation rather than categorical institutional resistance. Combined with the high share of personal initiative, the result depicts an environment in which employees may experiment, but without a sufficiently clear organisational framework for doing so.

These data are also important from the perspective of institutional learning. When experimentation depends primarily on individual employees, accumulated experience may remain confined to a particular person or team. Successful solutions are difficult to disseminate, while unsuccessful attempts may remain undocumented and fail to

contribute to subsequent improvements in institutional decisions. The absence of a clear framework thus constrains not only AI use, but also the institution's ability to learn systematically from its own experiments. This tension is well established in organisational learning theory: exploration of new possibilities entails search, experimentation, and acceptance of uncertainty, whereas the exploitation of established solutions is associated with refinement, efficiency, and execution. March characterises exploitation as 'the refinement and extension of existing competences, technologies, and paradigms', whose returns are 'positive, proximate, and predictable'; exploration is 'experimentation with new alternatives', with returns that are 'uncertain, distant, and often negative' (March, 1991, p. 85). Institutional support for controlled experimentation is therefore important not only for innovation, but also for maintaining the organisation's ability to learn and develop new solutions.

Experimentation should, of course, not be encouraged unconditionally. Rather, the data support the need for managed experimentation in which the purpose of the test, permitted applications and data, responsible persons, the method for verifying results, and the criteria for continuation, redesign or termination are defined in advance.

Within such a framework, experimentation can enable new applications to be tested safely while also creating organisational knowledge. Accumulated practical experience can then be documented, evaluated and shared, and decisions on subsequent implementation can be based on the results of the tests conducted rather than solely on individual initiative.



CHAPTER 3

OBSERVATIONS AND CONCLUSIONS

The study identifies positive but uneven change. Management support, practical AI use, and employees' reported willingness are developing more markedly than resource provision, internal rules, the allocation of responsibilities, and control mechanisms. The principal governance risk does not arise from AI use itself, but from the expansion of use while institutional mechanisms for guiding and controlling it remain underdeveloped.

A substantial share of AI use takes place through personal access, while institution-provided channels remain limited. This creates conditions in which practice may develop faster than mechanisms for approval, allocation of responsibilities, data protection, and monitoring of outcomes. At the same time, the data show the importance of other prerequisites for sustainable implementation, including suitable data, integrated systems, skills, and governance capacity.

Comparison between reported willingness to undertake practical work with AI (56.6%), regular or limited use in specific activities (18.1%), and positive ratings of the existence of basic governance mechanisms for AI projects (approximately 13–15%) reveals a substantial gap between individual willingness and organisational conditions. Employee motivation can therefore hardly be regarded as the principal constraint. The data instead draw attention to the organisational conditions required for the next stage of development, including authorised access, clear rules, institutional support, and accountability mechanisms.

Underdeveloped mechanisms for sharing and documenting experience limit the ability of individual experiments to develop into sustainable organisational knowledge.

The comparative chart presents three harmonised indicators for 2025 and 2026: regular or limited AI use in specific activities, perceived organisational readiness, and willingness to undertake practical work with AI. The data represent two repeated cross-sectional surveys with independent samples rather than longitudinal tracking of the same individuals. The differences should therefore be interpreted as descriptive changes between the two survey rounds.

USE OF AI IS RISING FASTER THAN ORGANISATIONAL READINESS

Three headline comparisons, 2025–2026

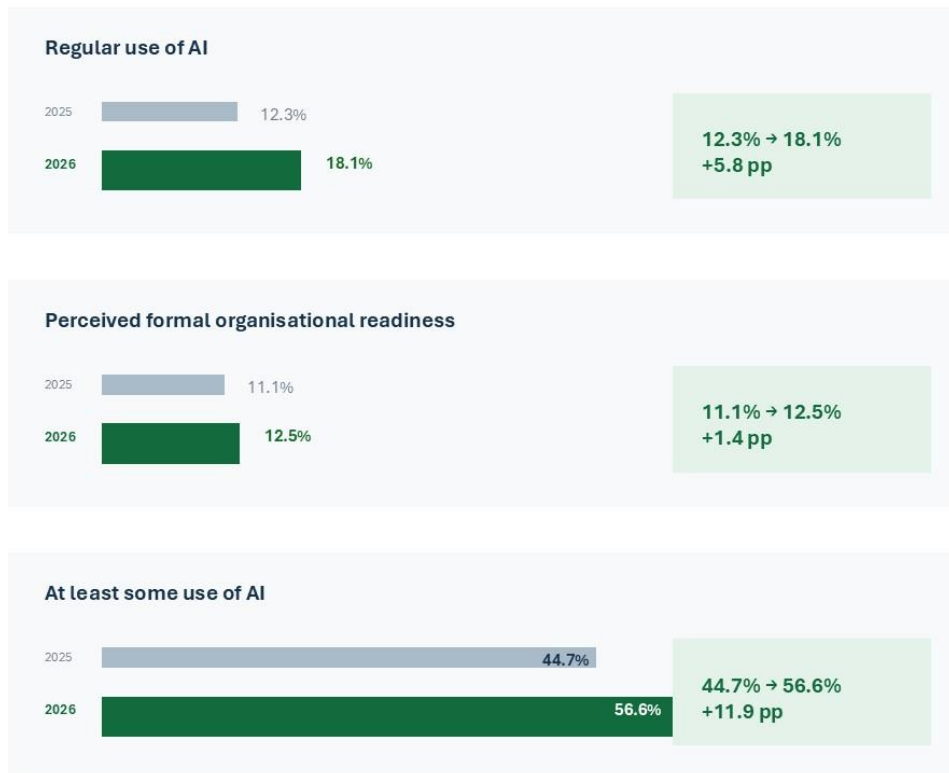


Figure 23 . Comparative chart showing perceived organisational and individual readiness

The comparison is particularly revealing because of the different magnitude of these changes. Regular or limited use increases from 12.3% to 18.1% (+5.8 percentage points), while willingness to undertake practical work with AI rises from 44.7% to 56.6% (+11.9 percentage points). Perceived organisational readiness increases from 11.1% to 12.5% (+1.4 percentage points). The data therefore do not indicate an absence of progress, but rather asymmetric progress: willingness to participate and practical use are changing more markedly than the institutional conditions required for their sustainable and responsible development.

The study by Mikalef et al. (2026, p. 21) shows a similar dynamic: where formal rules are absent, fragmented or unclear, informal practices and norms emerge around actual AI use, while organisational guidance may lag behind employee behaviour.

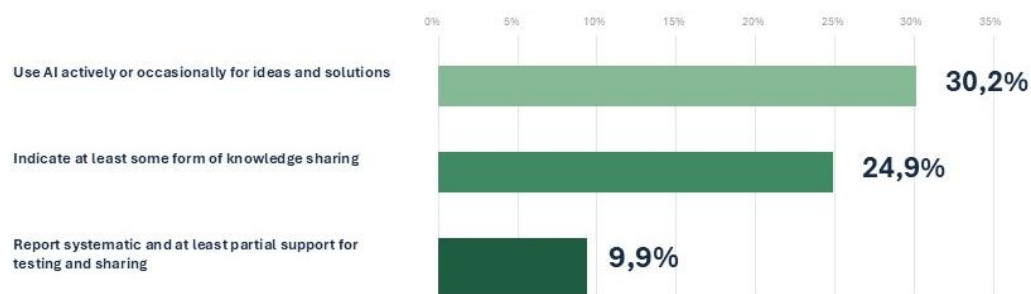


Figure 24. Comparative chart on institutional knowledge sharing in the field of AI

Bulgarian public administration is not an exception to a broader international trend. The development of AI is outpacing the establishment of mechanisms for its responsible governance. The Stanford AI Index 2026 reports that responsible-AI infrastructure is failing to keep pace with deployment, while documented AI incidents increased in 2025 (Stanford HAI, 2026, pp. 126, 129). The OECD.AI Index likewise identifies substantial gaps in the measurement of trustworthy AI, including in relation to inclusiveness, human rights, transparency, sustainability, and accountability (OECD, 2026b, p. 12).

This is a familiar challenge in technological change in the public sector. Many administrations are still building the necessary combination of policy, governance, and technological solutions for digital transformation (Carter, Desouza, Dawson & Pardo, 2024, p. 2). In the case of AI, the task is even more complex because its effective use depends simultaneously on technological, organisational, legal, ethical, and societal conditions (Wirtz et al., 2019, p. 601). This points to the need for AI use to develop only alongside the capacity to govern it. It must be clear for what purposes AI may be used, with what data, through which tools, who verifies the output, and who bears responsibility. Authorised and secure access, clear rules, defined responsibilities and appropriate monitoring mechanisms are required.

The result of 49 out of 100 should be viewed in precisely this perspective. It is not a final assessment, but an indication of the stage at which public administration currently stands. Human potential and practical use are increasing; the next task is to convert them into sustainable institutional capacity. Success will not be measured by the number of AI tools implemented, but by whether they lead to better services and decisions and more efficient work, while at the same time ensuring accountability, protection of rights, and public trust. In international models of organisational maturity, it is precisely the transition from practices dependent on individual people to documented, repeatable and governed processes that distinguishes initial experimentation from institutional capacity (UNESCO, 2025, pp. 7–8).

CHAPTER 4

PRIORITIES FOR THE NEXT STAGE OF DEVELOPMENT

2026



The Index results indicate positive but uneven change. Practical AI use and employees' willingness are developing faster than internal rules, secure institutional access, the allocation of responsibilities, and mechanisms for sharing accumulated experience.

The next stage is not simply about expanding the use of technology. It requires building the capacity of the state to determine where AI delivers public benefit, under what conditions it may be used, and who bears responsibility for the outcome.

1. A common national direction and clear responsibility

The use of AI raises issues relating to data, e-government, cybersecurity, public procurement, skills, and the protection of fundamental rights. When these issues are addressed separately, institutions may develop incompatible practices while common problems remain unresolved.

Cross-government coordination is therefore needed to connect national priorities with administrative practice, identify systemic risks and propose solutions to issues requiring action by more than one institution. A National AI Coordinator should be designated to ensure this consistency and public accountability, without replacing the powers of the competent authorities or the responsibility of each administration for a specific application.

2. Internal direction, rules, and management responsibility

National policy and shared capacity cannot and should not replace management decision-making within each administration. Every institution must have a clear internal direction for AI use, aligned with its functions, the public problems it addresses, the data available to it, and the risks to citizens. Not every administration needs to develop an extensive standalone strategy. What is needed are concise, workable internal rules approved by management, specifying the purposes for which AI may be used, which tools and data are permitted, who is responsible for specific applications, how human oversight is exercised, and how employees may propose pilot initiatives. These rules should be based on a common national model, while being applied in accordance with the size, functions, and risk profile of the administration concerned. In this way, the rules will not be a formal requirement, but a practical basis for secure work, clear responsibility, and better decisions.

3. Demonstrable public benefit before wider use

AI should be used where it helps address a specific public problem and where it is more appropriate than a non-AI alternative. This requires every significant pilot initiative to have a clear objective, defined scope, designated responsible persons, success criteria, and termination conditions.

The National AI Laboratory should provide the conditions for such assessment. It must give administrations access to shared expertise and a secure environment in which the data, security, quality of outputs, impact on citizens, and practical applicability of the solution can be assessed.

The formal AI regulatory sandbox under the AI Act should also be organised within the National AI Laboratory. Pursuant to Article 57 of Regulation (EU) 2024/1689, as amended by Regulation (EU) 2026/1744, Bulgaria must ensure that at least one national AI regulatory sandbox is operational by 2 August 2027. It applies in cases where the involvement of a competent authority and controlled clarification of the applicable rules are required. An ordinary pilot initiative within public administration is not a regulatory sandbox and should not be presented as one..

4. Human responsibility and protection of citizens

A public institution cannot transfer its responsibility to an algorithm, an external provider or a central expert body. The public objective, the acceptable level of risk, and the final decision are determined by the people and institutions that bear democratic and legal responsibility.

Each administration must determine who is responsible for a specific AI application, how human oversight is exercised, and how the system's output can be reviewed or corrected. Where decisions have a significant impact on people, human judgement cannot be merely formal. It must be supported by information, sufficient time and genuine authority to intervene.

Trust also requires an appropriate degree of transparency. Citizens must be able to understand where and for what purposes AI is being used, which institution bears responsibility, and how they can request an explanation or report a problem.

5. Institutional learning and reuse of solutions

Accumulated practical experience has value only when it becomes shared institutional knowledge. Organisational learning requires this transition to be managed deliberately, and accumulated experience must be capable of being shared among employees and units, retained in organisational memory and gradually embedded in systems, procedures, and sustainable practices. The Index shows that mechanisms for sharing and documenting experience remain limited, increasing the risk that different administrations may repeat the same mistakes or redevelop similar solutions.

After every significant pilot initiative, a documented decision must be taken on termination, redesign, limited use, preparation for wider use or reuse by other administrations. Successful, unsuccessful, and discontinued cases should feed into common methodologies, training, contractual clauses, and decisions on reuse.

In this way, AI use will not remain a series of isolated technological initiatives but will become part of the state's capacity to improve services, administrative processes, and public decision-making.

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DATA AVAILABILITY STATEMENT

The data supporting the conclusions of this study are freely available on Zenodo at <https://doi.org/10.5281/zenodo.22026174>, DOI: 10.5281/zenodo.22026174.



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