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Public servants' attitudes toward the use of Artificial Intelligence in policymaking: An experimental study

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ABSTRACT

Artificial Intelligence (AI) is becoming increasingly integrated into various aspects of society, including public policy processes. However, little is known about public servants' views on the use and implementation of AI. We conducted an experimental study among UK public servants ($N = 801$) to examine how attitudes toward different levels of AI involvement vary across the phases of the policy cycle and how the provision of information influences these attitudes. Our findings are threefold. First, we observed significant skepticism toward more extensive forms of AI involvement. That is, public servants' attitudes became less favorable as AI's role and/or weight in policymaking increased, particularly when AI moved beyond providing advice and support. Secondly, attitudes toward AI involvement were least positive during the policy decision-making phase, whereas AI involvement in the policy evaluation phase was viewed most positively. Thirdly, public servants who received information about AI's potential applications expressed more positive attitudes than those who did not receive such information. In sum, the present study demonstrates a cautious attitude among public servants toward deeper AI integration in public policy processes, which can at least partly be improved through targeted information about AI's potential applications.

1. Introduction

Artificial Intelligence (AI) becomes a central element of contemporary technological advancement, impacting virtually every societal domain. One area where the potential of AI is particularly promising, yet relatively underexplored, is in the public sector (Dwivedi et al., 2021; Sun & Medaglia, 2019; Wirtz & Müller, 2019). Although there is no single definition of AI, in public policymaking AI is generally defined as "systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals" (European Commission, 2018; also see Zuiderwijk et al., 2021). In this study, AI is treated as an umbrella concept that encompasses a range of computational and data-driven techniques, including machine learning, natural language processing, robotics, and cognitive computing. As part of this spectrum, conversational and generative AI applications represent a contemporary example of AI technologies that are particularly relevant for public servants in their interactions with AI systems. As such, this broad framing captures both the diversity of AI technologies being introduced into public sector workflows and the growing prominence of generative AI applications, which, due to their widespread use (Bright et al., 2024), are likely to shape public servants' attitudes toward AI.

Governments across the globe are increasingly exploring AI applications to improve public service delivery, enhance internal management, and support policymaking processes (see van Noordt & Misuraca, 2022; Wirtz et al., 2019). For instance, AI-based technologies have been used to improve communication between government and citizens in Greece (Androutsopoulou et al., 2019), automate administrative tasks like tax filings in Estonia (Rafik, 2024), and predict and manage traffic flows in 'smart cities' like Singapore and Zurich (Herath & Mittal, 2022). These cases illustrate the transformative potential of emerging AI technologies across various policy domains and on different levels of government, from the federal (e.g., Khan et al., 2024) to the local level (e.g., Vogl et al., 2020).

Similar developments can also be observed in the United Kingdom (UK), where AI technologies are becoming increasingly embedded in public sector practices. A recent report by the Cabinet Office, for instance, indicates that over a third (37%) of UK government bodies are

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actively using AI, with an additional third (37%) either piloting or planning AI deployment (National Audit Office, 2024; see also Engstrom et al., 2020, for comparable findings in the US). This growing uptake highlights that AI is not merely a theoretical concern but a timely and relevant issue for UK public administration; underscoring the importance of understanding how public servants perceive and respond to its integration into policymaking.

Despite this growing uptake, a recent literature review (Chandra & Feng, 2025) found that most studies in this domain have been qualitative, exploratory, or conceptual, with relatively few employing empirical methodologies. This lack of empirical evidence leaves open important questions about how public servants actually perceive and respond to AI in practice. In addressing this gap, we focus on public servants' AI adoption attitudes rather than their formal technology acceptance, aiming to capture how they view and respond to AI usage in policymaking.[1] More specifically, we empirically examine how UK public servants' attitudes are shaped by the level of AI involvement, the stage of the policymaking cycle, and the availability of information. In this context, we adopt a broad view of public policy that spans multiple levels of government, from local codes and municipal regulations to national legislation. To capture this diversity, our sample includes more than 800 UK public servants from local, state, and federal government agencies, providing a broad view of public servants' attitudes toward AI across different settings.

1.1. Public servants' perceptions of AI involvement

Successful implementation of AI in the public sector heavily depends on the perceptions and attitudes of public servants, who play a pivotal role in advising, implementing, and evaluating public policies. As key actors in government processes, their acceptance or rejection of new technologies can significantly influence the success of AI in policymaking (Mergel et al., 2019). In fact, public servants' unique position allows them to directly shape the effective integration of such technologies (Ahn & Chen, 2022). If they are skeptical or resistant, the successful adoption of AI could be hindered, despite its potential benefits. Conversely, if public servants are supportive of AI usage, they can become champions for its adoption, facilitating smoother transition and greater overall effectiveness.

Despite the critical role that public servants play in the implementation and adaptation of AI-based technologies; this professional group remains an understudied population. Indeed, most prior studies on the use of AI in the public sector have primarily focused on citizens' perspectives (e.g., see Gaozhao et al., 2024; Gesk & Leyer, 2022; Grimmelikhuijsen, 2023; Haesevoets et al., 2024; Ingrams et al., 2022; Kleizen et al., 2023; Lehtiö et al., 2023; Schiff et al., 2023; Tao et al., 2024; Waldman & Martin, 2022; Wang et al., 2024). Yet, as Ahn and Chen (2022, p. 2) recently pointed out, "little is known about how the emerging AI technologies are perceived by those who work in the public sector." This sentiment is also echoed by Ruvalcaba-Gomez and Cifuentes-Faura (2023) and by van Noordt and Misuraca (2022), who have advocated for further academic inquiry into public servants' perceptions regarding the use of AI in public policy processes, an issue the present study directly taps into.

Recent studies have shown a notable rise in research focused on how people working in the public sector perceive the integration of AI, with most findings indicating a rather positive stance. For instance, Ahn and Chen (2022) reported that a significant majority of US government workers support AI implementation within their agencies. Similarly, Ruvalcaba-Gomez and Cifuentes-Faura (2023) found that a large number of public sector employees in Jalisco, Mexico, are fully receptive to AI integration. In a comparable vein, Criado and de Zarate-Alcarazo (2022) observed that CIOs in Spanish local governments are highly receptive to AI adoption. Likewise, Distor et al. (2021) also identified a strong behavioral intention to use AI technologies among public servants in Carmona, Philippines.

While these prior studies all suggest a *'generally'* positive outlook toward the adoption of AI among public servants, their assessments often lacked depth. In most cases, public servants' attitudes were measured using a broad, single-item question. For instance, Ahn and Chen asked their respondents (on a scale of 1 to 7): "I will support the implementation of AI in the government agency that I work for," while Ruvalcaba-Gomez and Cifuentes-Faura asked respondents to rate (on a similar scale) to what extent they are "fully open to the introduction of Artificial Intelligence."

In this context, it is important to note that public servants' more '*specific*' perceptions of AI may actually vary depending on a wide variety of factors. To address this, our study moves beyond general measures of support and instead focuses on three underlying dimensions that may shape AI adoption attitudes. First, rather than treating AI as a uniform, all-or-nothing intervention, we differentiate between *varying levels of AI involvement*, ranging from limited supporting roles to more extensive decision-shaping functions. This distinction allows us to examine how attitudes differ depending on the degree to which AI is integrated into governmental tasks. Secondly, we analyze whether public servants evaluate AI differently depending on *the stage of the policymaking process* in which it is introduced (agenda-setting, policy formulation, decision-making, implementation, or evaluation), thereby contextualizing their attitudes within specific phases of the policymaking cycle. Thirdly, we examine whether *providing information* about AI's potential applications and functionalities influences how public servants evaluate the use of AI. To this end, we experimentally compare a condition in which participants receive detailed information about AI's possible applications with a condition in which no such information is provided.

2. Theoretical background and hypotheses development

To provide a deeper understanding of how public servants' view AI, this study moves beyond the scope of typical single-focus investigations. Instead of examining AI adoption attitudes through a single theoretical lens or isolated factor, we adopt a holistic, multidimensional perspective that considers how multiple interrelated dimensions jointly shape evaluations. As outlined above, our empirical design examines three key dimensions (i.e., level of AI involvement, stages of the policymaking cycle, and information availability), which together provide a richer and more nuanced understanding of the conditions under which public servants are more or less receptive to AI integration. The following sections discuss each dimension in detail, highlighting relevant theory and prior evidence that informs our hypotheses.

2.1. Level of AI involvement

A central dimension shaping public servants' AI adoption attitudes concerns the degree of AI involvement in policymaking processes. Rather than treating AI involvement as binary—either fully present or entirely absent—it is more accurate to conceptualize it as a continuum of collaboration between human and artificial agents. Along this spectrum, the relative influence of AI varies from minimal assistance to near-complete autonomy (see Haesevoets et al., 2021; Li et al., 2017; Raisch & Krakowski, 2021), with each position implying a distinct distribution of authority, responsibility, and control.

At the lowest end of the spectrum, there is no AI involvement: human officials make judgments independently, relying on their professional expertise, experience, and established bureaucratic routines. AI may still exist in the organizational environment but plays no meaningful role in shaping policy processes. This stage represents the traditional model of

[1] In the context of this work, the term '*public servants*' is used to refer to government employees working at the local, regional, or federal level, specifically within the Government & Public Administration sector.

governance, where accountability and discretion remain exclusively human. Moving one step further, AI may assume a supporting or advisory role. In such configurations, AI systems generate insights, forecasts, or recommendations that inform but do not replace human decision-making. This 'supportive framework' (cf. Waefler et al., 2025) exemplifies a collaborative relationship in which AI operates as a consultant. A third level reflects shared or co-decisive arrangements, in which human and AI actors jointly contribute to the policymaking process. Here, responsibilities are distributed, with AI offering data-driven analyses and humans integrating contextual knowledge, values, and ethical reasoning. This corresponds to ideas of 'hybrid intelligence' and 'human-AI teaming' (e.g., Berretta et al., 2023; Christoffersen & Woods, 2002), where decisions emerge from interactive collaboration rather than unilateral control. At the two highest levels of the continuum, AI takes on a dominant or even autonomous role, exercising substantial decision-making power, either with or without human oversight. Systems at this stage analyze data, identify policy options, and may even implement chosen courses of action with minimal or no human interference. While formal oversight mechanisms may remain in place, they tend to operate ex post rather than ex ante, limiting the practical ability of humans to intervene. Such forms of 'algorithmic governance' (e.g., Danaher et al., 2017) maximize efficiency but raise fundamental questions about democratic legitimacy, fairness, and the visibility of underlying decision logics (see Busuioc, 2021).

Conceptualizing AI involvement as a graduated spectrum underscores that the delegation of decision-making authority to AI is not an all-or-nothing phenomenon. Rather, it reflects an evolving continuum of collaboration between human and artificial agents, with each level entailing distinct implications for perceptions of control, trust, and responsibility. In the present study, this dimension is explicitly embedded in our empirical design and examined alongside two additional dimensions introduced in the following sections, namely: the stage of the policymaking cycle in which AI is applied (Section 2.2) and the availability of information about its potential use (Section 2.3). Considering these three aspects together in a multidimensional perspective allows for a more comprehensive understanding and nuanced account of the circumstances in which public servants view the use of AI favorable or unfavorable.

2.2. Integrating AI into the policy cycle framework

To understand how AI may shape public policymaking, it is important to consider the policymaking process itself. The policy cycle framework provides a structured lens for examining the key stages of policy development and implementation, offering a clear way to contextualize and analyze the potential impacts of AI at each stage. Typically, the policy cycle is divided into five phases: agenda-setting, policy formulation, policy decision-making, policy implementation, and policy evaluation (Howlett & Giest, 2012; Jann & Wegrich, 2017). Based on Anderson (1974) and Valle-Cruz et al. (2020), below we elaborate on these phases as well as on how AI can be integrated into each phase.

The first phase of the policy cycle is the *agenda-setting* phase, which involves identifying issues that require governmental attention and prioritizing them on the public agenda. During this initial stage, AI-based technologies can be implemented to analyze vast amounts of data from various sources such as social media, news articles, and public opinion surveys to detect emerging trends and pressing social issues. The second phase, the *policy formulation* phase, involves developing potential solutions to the identified issues. AI can contribute to this phase by simulating policy outcomes, analyzing the potential impacts of various policy options, and providing data-driven recommendations. The third phase concerns the *policy decision-making* phase. This phase involves selecting the most appropriate policy option from the alternatives developed during the policy formulation phase. It requires careful consideration of the potential benefits and drawbacks of each option. AI can contribute to this phase by offering predictive analytics and risk assessments, as such leading to more informed choices. AI's role in the decision-making phase is thus more about selecting options, rather than simply generating them. The fourth phase is the *policy implementation* phase. During this stage, the decision made earlier will be put into practice. Real-time data analytics and monitoring systems powered by AI can track the implementation process, guiding the most efficient implementation strategy. The fifth and final phase of the policy cycle is the *policy evaluation* phase, which involves assessing the effectiveness of the implemented policies. Here, AI can play a significant role by monitoring and evaluating policy outcomes, providing real-time data analysis, and identifying areas for further improvement or adjustment. Table 1 provides specific, real-life examples of AI usage for each phase of the policy cycle.

The traditional policymaking cycle provides a structured lens for examining how AI may influence government functioning across all stages of policy development and implementation. Integrating this well-established framework with the emerging influence of AI (cf. Table 1) highlights that AI has the potential to transform government operations at every stage of the cycle: from enhancing the agenda-setting phase with data-driven insights to strengthening policy evaluations through rigorous outcome analysis. Each stage, however, also presents distinct opportunities and challenges (see Busuioc, 2021; Valle-Cruz et al., 2020; Wirtz et al., 2019), suggesting that public servants' engagement with AI may vary systematically depending on the phase in which it is introduced.

It is therefore important to study public servants' attitudes toward AI use across these different stages of the policymaking cycle. Indeed, understanding public servants' attitudes is crucial because they act as critical intermediaries between AI tools and policy outcomes. Their expertise, trust, and professional judgment shape whether AI technologies are adopted or resisted. Given these dynamics, examining phase-specific variations is not only theoretically important but also practically relevant. It allows identification of stages where AI is likely to be embraced and informs how AI tools can be designed and implemented in alignment with public servants' roles, responsibilities, and expectations.

Building on scholarship distinguishing between analytical and political stages of the policy process (e.g., Howlett et al., 2009; Valle-Cruz et al., 2020), as well as broader work on the role of digital technologies in public administration (e.g., Bovens & Zouridis, 2002; Wirtz et al., 2019), we expect that public servants' attitudes toward AI will vary depending on the policy phase in which AI is applied. Task characteristics differ systematically across these phases: some stages, such as agenda-setting and evaluation, are primarily analytical and information-driven, whereas others, such as decision-making, are more political and normative. Busuioc (2021) further observes that in high-accountability contexts, public servants are less inclined to delegate discretion to algorithms, highlighting the tension between automation and professional responsibility.

Drawing on this literature, we expect AI to be most positively received during agenda-setting and policy evaluation. These phases involve information gathering, pattern detection, forecasting, and performance assessment (Birkland, 2017; Wollmann, 2017), tasks that are comparatively structured and align closely with AI's data-processing and predictive capabilities (Valle-Cruz et al., 2020). In such contexts, AI is likely to be perceived as augmenting rather than replacing bureaucratic judgment. Conversely, AI use is expected to be received least favorably during policy decision-making. This phase entails normative trade-offs, political contestation, and heightened accountability, all of which increase the perceived risks of delegating discretion to algorithmic systems (Busuioc, 2021; Wirtz et al., 2019). Here, AI involvement may be viewed as constraining human judgment or complicating responsibility attribution (Matthias, 2004). Finally, policy formulation and implementation are expected to occupy an intermediate position. While both phases contain analytical and operational components that may benefit from AI-supported modeling and process optimization (Valle-Cruz et al.,

Table 1
Examples of AI applications at different stages of the policy cycle (own elaboration based on Valle-Cruz et al., 2020).

Phases	Cases/Examples	Case descriptions
1. Agenda-setting	Tracking of virus outbreaks (Greenemeier, 2014).	The HealthMap to track the Ebola Outbreak in Africa relies on disease surveillance websites that act as key hubs for information processing. These sites use a combination of AI software and human expertise to track, report, and map information related to public health crises, often faster than government ministries and international organizations.
2. Policy formulation	Simulation of urban planning policies (Son et al., 2023)	Urban planners can use AI models to simulate traffic flows based on different urban development plans. By inputting various policy options, such as new road construction or changes in public transportation routes, AI can predict traffic congestion, travel times, and emissions. This can help urban planners in generating effective policies for reducing traffic and improving air quality.
3. Policy decision-making	AI-powered military drone (Surender, 2024)	AI has a significant impact on the autonomous navigation capabilities of military drones. These advanced systems enable unmanned aerial vehicles (UAVs) to operate with minimal human intervention, enhancing their effectiveness in complex environments. By leveraging cutting-edge algorithms and sensor technologies, AI-powered drones can make split-second decisions, adapt to changing conditions, and execute missions with unprecedented precision.
4. Policy implementation	Implementation of smart police stations (Banerjee, 2024)	In Dubai, smart police stations are run entirely by AI-powered robots. The smart police station, which is in operation 24/7, provides services like crime reporting, lost-and-found requests, and victim support. Additionally, it receives work and income complaints and home security requests.
5. Policy evaluation	Evaluation of environmental policies (Swisscontact, 2021)	AI technologies have recently been used to evaluate the environmental impact of electric vs. diesel buses in public transport in Santiago de Chile, a city that is striving to improve air quality and reduce carbon emissions.

Note. While the present table portrays the policy cycle as a linear process, it is important to note that, in reality, the phases may overlap and interact in complex ways, with feedback loops between stages.

2020), they also involve coordination, contextual interpretation, and adaptive discretion (Hill & Hupe, 2021). As such, AI is expected to be evaluated more positively than in decision-making, but less positively than in agenda-setting and evaluation. Based on this reasoning, we formulate the following comparative hypothesis that explicitly contrasts attitudes across the five policy phases:

Hypothesis 1. Public servants are expected to express the most positive attitudes toward increasing levels of AI involvement in the agenda-setting and policy evaluation phases, moderately positive attitudes in the policy formulation and policy implementation phases, and the least positive attitudes in the policy decision-making phase.

2.3. The role of information in shaping attitudes toward AI

Another important factor to consider in examining the impact of AI on public policy processes is the availability of information. Information availability effects, which have been studied across various domains, highlight how being 'informed' or 'uninformed' about a particular topic can substantially impact individuals' opinions and decisions (for examples, see Abelsson et al., 2020; Cantor & Macdonald, 2009; Fischer & Döring, 2022; Murnighan & Roth, 1977; Qadir & Quadri, 2016). For instance, in psychology, the availability of information has been shown to reduce cognitive biases and improve decision-making processes (Hilbert, 2012). In healthcare, research indicates that patients with access to comprehensive information about their conditions and treatments tend to achieve better health outcomes (Nguyen et al., 2017; Street Jr et al., 2009). Similarly, marketing studies have shown that informed consumers are more likely to make rational purchasing decisions (Clemons & Gao, 2008). These examples illustrate the profound impact that the availability of information has on people's attitudes, beliefs, and behaviors.

In the public sector, providing information about AI's potential applications may likewise influence how public servants evaluate and respond to AI tools. Although, to the best of our knowledge, no experimental studies have directly tested the effects of information availability among public servants, evidence from studies with citizens suggests that informational cues can meaningfully influence attitudes and intentions. For instance, Aoki (2020) found that communicating specific purposes for government chatbots—such as ensuring uniformity of responses or improving 24/7 accessibility—modestly increased public trust compared to conditions with no communicated purpose. Similarly, Palm et al. (2025) showed that participants who received information about different AI application areas reported higher usage intentions than those who received no such information.

Drawing on this prior research, we expect that providing concrete information about AI applications will foster more positive and nuanced attitudes among public servants. That is, well-informed public servants are anticipated to be more open to extensive AI involvement across different stages of the policy cycle, whereas those without relevant information may adopt a more cautious or negative stance. In line with this reasoning, we formulate the following hypothesis:

Hypothesis 2. Public servants are expected to express more positive attitudes toward increasing levels of AI involvement when provided with information about AI's potential applications and functionality, compared to when no such information is provided.

3. Method

3.1. Recruitment strategy, sample, and design

The study was administered in Spring 2024. A total of 828 respondents were recruited through Prolific, an online research platform that provides a detailed description of the characteristics of their participant pool (see Palan & Schitter, 2018, for more details on this platform). Respondents were selected by means of the screening criteria provided by Prolific, which cover a wide range of variables, including those related to respondents' location and employment status. To be eligible for the present study, respondents had to meet the following three criteria: (1) reside in the UK ('location'), (2) hold a position as either a local government employee, state government employee, or federal government employee ('employer type'), *and* (3) work specifically within the Government & Public Administration sector ('employment sector'). This focus was deliberately chosen because employees in this sector are most directly involved in policy processes and

therefore more familiar with the stages of the policy cycle examined in this study. Consequently, individuals employed in frontline public services (e.g., education, healthcare, law enforcement, etc.) were intentionally excluded. Participants received a payment of £2 for completing the survey.

Twenty-seven respondents (3.3%) were excluded from the analyses because they failed our included attention check (i.e., *"please select the first response option for this question"*).[2] The final sample therefore consisted of 801 respondents. Respondents had a median age of 39 years, 63.7% were female, 68.7% obtained a bachelor's degree or higher, and 42.2% had been employed by the government for more than 10 years. Most respondents were employed at the local level (54.6%), followed by the state level (24.6%), and finally the federal level (20.8%). Compared with available UK civil servant workforce population benchmarks (UK Government, 2025), our sample includes a slightly higher proportion of females (63.7% vs. 54.6%) and was somewhat younger (median age 39 vs. 44 years). More details on the characteristics of the sample can be found in Appendix A.

Of the 801 respondents, 408 (50.9%) were assigned to the *'no application information'* condition (henceforth referred to as the *'no info'* condition), in which no further information was provided on how AI can be applied in the different phases of the policy cycle. The remaining 393 respondents (49.1%) were assigned to the *'application information'* condition (henceforth referred to as the *'info'* condition), in which information was provided explaining specifically how AI can be applied in each of the five policy cycle phases (see Section 3.2 for more details). Overall, the two groups were largely comparable on key demographic characteristics. Small differences were observed for age and tenure: respondents in the *'no info'* condition were slightly older (median = 41 years) and had longer tenure (median = 11–20 years) than those in the *'info'* condition (median age = 37 years; median tenure = 6–10 years). No meaningful differences were found for gender, education, or employer type (see Appendix A for detailed descriptive statistics). The dataset and data analysis scripts of our study are made publicly available and can be accessed through Open Science Framework: https://osf.io/swk5d/overview.

3.2. Procedure

The experimental flow of our study is shown in Fig. 1. At the outset of the study, respondents were asked to give their informed consent. They were then questioned about their gender, age, education level, seniority, and whether they were a local, state, or federal government employee. Next, respondents were presented with a brief introductory statement (see below), which also included a general definition of AI. We adopted this approach to ensure a shared understanding of the concept among respondents (for a similar approach, see Haesevoets et al., 2024; also see Lee, 2018).

> "The policy cycle is a framework that is used for understanding the policy process. It consists of five different phases: agenda-setting, policy formulation, policy decision-making, policy implementation, and policy evaluation. In each of these five phases, Artificial Intelligence (AI) and human agents can be involved to varying degrees as well as in different roles. AI is a software system that uses algorithms that can infer problem-specific rules and create automated scoring to reach a decision."

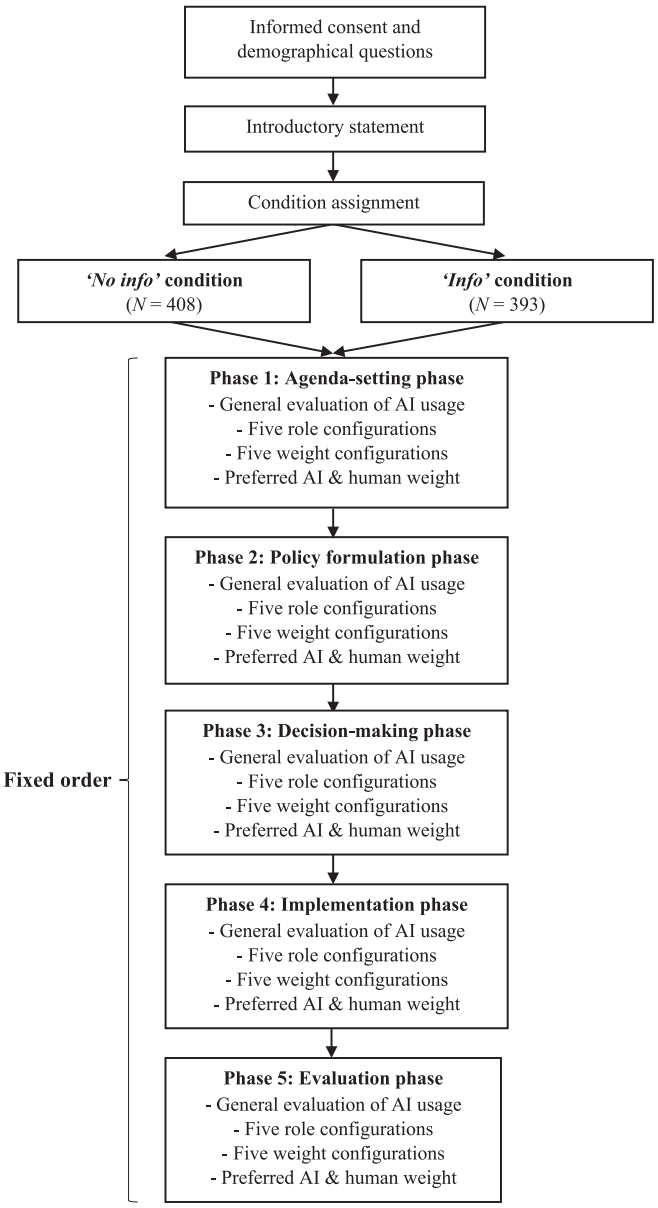

Fig. 1. The experimental flow chart of the present study.
Note. The policy phases and the role/weight configurations were presented in a fixed order rather than randomized. This approach reflects the natural progression of the policy cycle and the increasing levels of AI involvement, ensuring clarity and consistency for respondents.

After reading this statement, respondents were assigned to either the *'no info'* condition or the *'info'* condition (information availability manipulation). In both conditions, respondents were subsequently presented with the five phases of the policy cycle. Because these phases (i.e., agenda setting, policy formulation, policy decision-making, policy implementation, and policy evaluation) naturally build upon one another, they were displayed in their logical sequential order rather than being randomized. This structure was chosen to reflect the inherent progression of the policy process and to help respondents maintain a clear understanding of the scenario throughout the survey.

Table 2 outlines the information provided to respondents in both conditions. In the *'no info'* condition, respondents only received a brief description of each policy cycle phase, without any information on AI's possible applications and without the addition of any filler text (see plain text in Table 2). In contrast, in the *'info'* condition, these descriptions were expanded with additional information detailing how AI

[2] Only one attention check question was included in the experiment, embedded within the policy cycle role acceptance items (implementation phase, between role configurations 3 and 4). No additional attention or manipulation checks were included, as the experimental manipulation concerned the presence versus absence of objective information rather than the manipulation of a psychological construct. In addition, the policy cycle phases were implemented as within-subject conditions, making repeated manipulation checks redundant and potentially disruptive to the survey flow.

Table 2
Descriptions presented to respondents: the plain text was presented to respondents in both conditions; the text in italics was solely presented to respondents in the *'info'* condition.

Phases	Phase descriptions
1. Agenda-setting	The first phase of the policy cycle is the agenda-setting phase. This stage concerns the recognition of certain subjects as a problem demanding further governmental attention. *During the agenda-setting phase, AI can track emerging social problems almost instantly by collecting and analyzing data from social media. AI algorithms can monitor public discourse, detect trends, analyze sentiment, and identify patterns. This allows to determine and prioritize public concerns that need to be addressed.*
2. Policy formulation	The second phase of the policy cycle is the policy formulation phase. This stage involves exploring a variation of options or alternative courses of action available for addressing the identified problem. *During the policy formulation phase, AI can analyze large datasets to find underlying causes and correlations, model potential outcomes of various policy options, and optimize strategies for maximum effectiveness. Additionally, AI can simulate the impact of different policy options, providing insights that weigh the benefits and drawbacks of each option.*
3. Policy decision-making	The third phase of the policy cycle is the policy decision-making phase. During this stage, a decision is made on the ultimate course of action. *During the policy decision-making phase, AI can provide evidence-based recommendations in choosing the best policy option. AI-driven systems can analyze complex data, offering predictive insights and scenario analyses to understand the likely outcomes of different alternatives. AI can also facilitate the comparison of policy alternatives by evaluating their efficiency, cost-effectiveness, and alignment with policy goals, ensuring that the chosen course of action is well-informed and strategically sound.*
4. Policy implementation	The fourth phase of the policy cycle is the policy implementation phase. During this stage, the ultimate decision made earlier will be put into practice. *During the policy implementation phase, AI can automate monitoring processes and ensure efficient policy execution. Real-time data analysis and monitoring systems powered by AI can track the implementation process, quickly identifying bottlenecks and inefficiencies.*
5. Policy evaluation	The fifth phase of the policy cycle is the policy evaluation phase. This final stage concerns assessing the effectiveness of a public policy in terms of its goals and results. *During the policy evaluation phase, AI can objectively measure the outcomes and impact of implemented policies. AI can compare actual results with expected goals using advanced statistical and predictive analytics, identifying success factors and areas for improvement.*

Note. The phase descriptions (plain text) were adapted from Anderson (1974); the possible AI applications (italics) are based on Valle-Cruz et al. (2020).

can potentially be applied in each phase (see italicized text in Table 2). Consistent with best practices in vignette methodology, the added content was kept as concise as possible and directly tied to the manipulation itself (Aguinis & Bradley, 2014; Atzmüller & Steiner, 2010).

3.3. Measures

While many prior studies on AI adoption have relied on single-item measures, our study adopts a more comprehensive approach. As shown in Fig. 1, for each phase of the policy cycle, we implemented four distinct measures to capture respondents' nuanced preferences regarding AI integration. These measures include: a general evaluation of AI usage (measured with four items; see Section 3.3.1), an evaluation of five *role* configurations (see Section 3.3.2), an evaluation of five *weight* configurations (see Section 3.3.3), and an assessment of the preferred balance of human and AI decision-making authority (measured with two scores; see Section 3.3.4). Together, these four measures yield 16 evaluations per policy phase (four for the general evaluation, five for role configurations, five for weight configurations, and two for the preferred human-AI division), resulting in a total of 80 evaluations across all five phases. Importantly, to facilitate comprehension and minimize cognitive burden, the role and weight configurations (representing gradually increasing levels of AI involvement; see Table 3 for details) were presented in a predefined, structured sequence rather than randomized, ensuring a coherent understanding of AI integration across the policy cycle. Below, we provide a detailed description of each measure.

3.3.1. General evaluation of AI usage

First, we measured respondents' general evaluation of AI usage in each phase of the policy cycle. To this end, for each policy cycle phase, after being presented with the phase description (see Table 2), participants were asked to answer the following four items, which were selected from Haesevoets et al.'s (2023) 'good governance' scale: "Overall, to what extent do you consider the use of AI to be: 'appropriate' (item 1), 'legitimate' (item 2), 'effective' (item 3), and 'efficient' (item 4)?" Respondents could answer each item on a ten-point Likert scale, ranging from (1) *not at all* to (10) *very much so*. Because factor analyses (using the Principal Axis Factoring method) revealed that, for each of the five phases, respondents' responses on these four items all loaded on one single factor (explained variances ranging from 88.4% to 92.4%), they were averaged into scale measures for each phase (Cronbach's alphas ranging from 0.96 to 0.97; see Appendix B for more details).

3.3.2. Evaluation of five different role configurations

For each phase of the policy cycle, respondents were subsequently asked to also evaluate five distinct *role* configurations (adapted from Haesevoets et al., 2025). As shown in Table 3, these role configurations progressively increased the role of AI, starting with 'no role for AI' and progressing to a 'fully autonomous role for AI', with three intermediate levels in between: 'AI in an advisory role', 'AI in a co-decisive role', and 'AI in a decisive role, but with human control'. For each configuration, respondents had to indicate on a ten-point Likert scale to what extent they were willing to accept the proposed role configuration (1 = *not at all*, 10 = *very much so*).

3.3.3. Evaluation of five different weight configurations

In addition to the role configurations, respondents were also asked to evaluate five distinct *weight* configurations (based on Haesevoets et al., 2021). These weight configurations ranged 0% to 100% AI weighting, in increments of 25% (see Table 3 for more details). For each configuration, respondents rated the extent to which they are willing to accept the proposed weight distribution (1 = *not at all*, 10 = *very much so*).

3.3.4. Preferred amount of human and AI involvement

Finally, for each policy cycle phase, we also assessed respondents' preferred amount of human *and* AI involvement using a constant-sum approach (for recent applications of this method, see Haesevoets et al., 2021, 2024). To this end, respondents were asked to indicate how much weight they prefer human agents and how much weight they prefer AI to have in each of the five policy cycle phases. Respondents provided a

Table 3
Overview of the role and weight configurations.

#	Role configurations	Weight configurations
1	AI has no role.	AI 0% weight; humans 100% weight.
2	AI has an advisory/supportive role.	AI 25% weight; humans 75% weight.
3	AI and humans have to come to a joint decision.	AI 50% weight; humans 50% weight.
4	AI has a decisive role, but with human control.	AI 75% weight; humans 25% weight.
5	AI has a fully autonomous role.	AI 100% weight; humans 0% weight.

percentage score between 0 and 100 for both humans and AI, where 0 indicated 'no influence' at all and 100 indicated 'full influence'. The total of these two scores had to equal 100.

4. Results

4.1. General evaluation of AI usage

First, a repeated-measures ANOVA with respondents' general evaluation (reflecting the mean score of the 'appropriate', 'legitimate', 'effective', and 'efficient' item) of the five policy cycle phases (agenda-setting, policy formulation, policy decision-making, policy implementation, and policy evaluation) as within-subjects factor, and the information availability manipulation (*'no info'* vs. *'info'* condition) as between-subjects factor was conducted. The results of this analysis are detailed in Table 4, with the observed effects being illustrated in Fig. 2.

As can be seen in Fig. 2, most scores are located around the scale's theoretical midpoint (i.e., value 5.5), indicating that, *in general*, UK public servants seem to have a rather neutral stance toward AI involvement in public policy processes. Interestingly, however, respondents' scores vary considerably across the five policy cycle phases as well as across the two information availability conditions. Regarding the five policy cycle phases, it was found that respondents evaluated the use of AI as most positive during the policy evaluation phase, followed by the policy formulation phase, the policy implementation phase, the agenda-setting phase, and lastly, the policy decision-making phase. Subsequent pairwise comparison analyses showed that all five phases differ significantly from each other (all $ps < 0.001$), except for the difference between the agenda-setting and the policy implementation phase ($p = 0.582$; see Appendix C for more details on these analyses). Moreover, for each of the five phases of the policy cycle, respondents' general evaluation of AI usage was significantly more positive in the *'info'* condition than in the *'no info'* condition (all $ps < 0.001$; see Appendix D for details on the performed pairwise comparison analyses).

4.1.1. Robustness across demographic subgroups

Additional subgroup analyses across gender, age, education, seniority, and employer type revealed consistent patterns in both the relative ordering of policy phases and the direction of the information effect (visualizations provided in Appendix E). While some variation in absolute mean levels across demographic groups was observed (e.g., in the *'info'* condition, younger and higher-educated respondents reported slightly higher acceptance of AI than older and lower-educated respondents across several policy phases; see Figs. E.2 and E.3 of Appendix E), the overall pattern of results – including the comparative effects across policy phases and conditions – remained stable.

4.2. Evaluation of the different role configurations

To examine respondents' reactions to increasing levels of AI involvement, we subsequently examined how they evaluated the five different *role* configurations. To this end, we conducted a repeated-measures ANOVA with the five policy cycle phases (agenda-setting, policy formulation, policy decision-making, policy implementation, and policy evaluation) and the five role configurations (AI no role, AI advisory role, AI co-decisive role, AI decisive role but with human control, and AI fully autonomous role) as within-subjects factors and the information availability manipulation (*'no info'* vs. *'info'* condition) as between-subjects factor. The results of this analysis are presented in Table 5, with Fig. 3 visualizing the effects obtained.

Several noteworthy findings emerged from the analyses. First and foremost, as shown in Fig. 3, *overall*, the acceptance scores steadily decline when the role of AI increases, which shows that the respondents have a rather skeptical stance toward more extensive forms of AI involvement. When comparing the different policy cycle phases with each other, it was found that this skepticism is most outspoken for the decision-making phase (represented by the orange lines), and least outspoken for the policy evaluation phase (represented by the green lines). Moreover, across phases, when comparing the two information availability conditions with each other, we found that this skepticism is also consistently more pronounced in the *'no info'* condition than in the *'info'* condition. In particular, respondents in the *'no info'* condition (Fig. 3; Panel A) are significantly *less* willing to accept of a configuration in which AI has an advisory role than a configuration in which AI has no role ($p < 0.001$); conversely, those the *'info'* condition (Fig. 3; Panel B) are significantly *more* willing to accept of a configuration in which AI has an advisory role than a configuration in which AI has no role ($p = 0.004$; see Appendix F for more details on the pairwise comparison results).

4.3. Evaluation of the different weight configurations

Next, to examine respondents' willingness to accept the different *weight* configurations, a repeated-measures ANOVA with the five policy cycle phases (agenda-setting, policy formulation, policy decision-making, policy implementation, and policy evaluation) and the five weight configurations (AI 0% weight, AI 25% weight, AI 50% weight, AI 75% weight, and AI 100% weight) as within-subjects factors and the information availability manipulation (*'no info'* vs. *'info'* condition) as between-subjects factor was conducted. The results are presented in Table 6; Fig. 4 visualizes the effects obtained.

As shown in Fig. 4, respondents also reacted rather skeptically toward an increased amount of AI involvement. Again, this skepticism was most evident during the policy decision-making phase (represented by the orange lines) and was least evident during the policy evaluation phase (represented by the green lines). Moreover, across phases, this skepticism was again more pronounced in the *'no info'* condition than in the *'info'* condition, with respondents in the *'no info'* condition (Fig. 4; Panel A) being significantly *less* willing to accept of a weight configuration in which AI has 25% weight than of a configuration in which AI has 0% weight ($p < 0.001$), whereas those in the *'info'* condition (see Fig. 4; Panel B) are *equally* willing to accept these two weight configurations ($p = 0.123$; see Appendix G for more details on the pairwise comparison results).

4.3.1. Comparison of the role and weight configuration results

When comparing the evaluations of the *role* configurations (see Fig. 3) with those of the *weight* configurations (see Fig. 4), it can be concluded that respondents actually rated both these configuration types very similarly. This illustrates a stable and consistently cautious attitude among respondents toward deeper AI integration, irrespective of whether they are considering more concrete role configurations or more abstract weight configurations.

4.4. Preferred amount of human and AI involvement

Finally, to investigate in more detail how much weight respondents prefer human agents and AI to have, *relative to each other*, a repeated-

Table 4
General evaluation of AI usage: results of the repeated-measures ANOVA with 'Policy Cycle Phases' as within-subject variable and 'Information Availability Condition' as between-subjects variable.

Effects	df	*F*	*p*	partial η^2
Information Availability Condition	1, 799	48.50	< 0.001	0.057
Policy Cycle Phases	4, 796	142.12	< 0.001	0.417
Phases × Condition	4, 796	1.06	0.378	0.005

Note. Similar findings were obtained when the standardized score of gender (1 = male, 2 = female/other), age, education level, seniority, and employer type (1 = local, 2 = state/federal) were included as covariates in the analysis (main effect of 'Condition': $F(1, 794) = 45.15$, $p < 0.001$, partial $\eta^2 = 0.054$; main effect of 'Phases': $F(4, 791) = 142.69$, $p < 0.001$, partial $\eta^2 = 0.419$; interaction term: $F(4, 791) = 1.30$, $p = 0.267$, partial $\eta^2 = 0.007$).

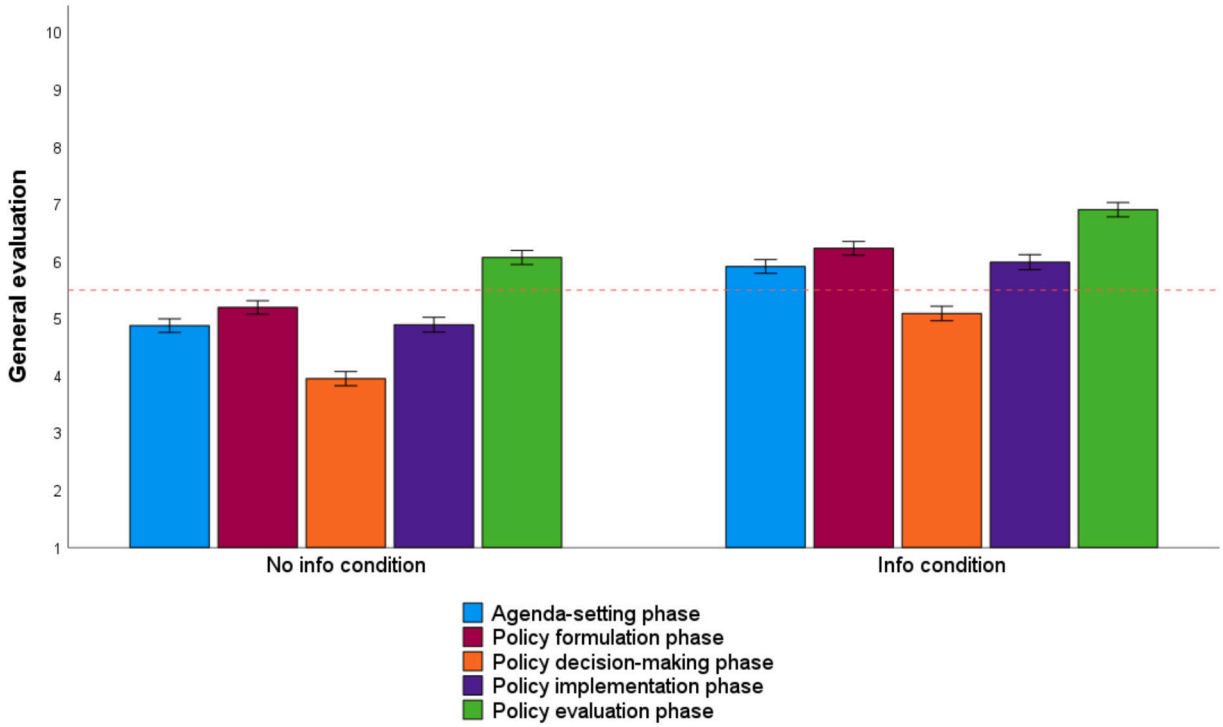

Fig. 2. Respondents' general evaluation (i.e., average of 'appropriate', 'legitimate', 'effective', and 'efficient' item) of AI usage (error bars reflect standard errors).

Table 5
Evaluation of the *role* configurations: Results of the repeated-measures ANOVA with 'Policy Cycle Phases' and 'Role Configurations' as within-subject variables and 'Information Availability Condition' as between-subjects variable.

Effects	df	*F*	*p*	partial η^2
Information Availability Condition	1, 799	2.15	0.143	0.003
Policy Cycle Phases	4, 796	65.55	< 0.001	0.239
Role Configurations	4, 796	576.17	< 0.001	0.743
Phases × Condition	4, 796	1.69	0.151	0.008
Role Configurations × Condition	4, 796	12.59	< 0.001	0.059
Phases × Role Configurations	16, 784	28.37	< 0.001	0.367
Phases × Role Configurations × Condition	16, 784	1.16	< 0.291	0.023

Note. A similar analysis with inclusion of the standardized covariates (i.e., gender, age, education level, seniority, and employer type) yielded similar results (i.e., all effects that were significant remained significant, whereas the non-significant effect of 'Condition', 'Phases × Condition', and 'Phases × Role Configurations × Condition' remained non-significant; $p = 0.197$, $p = 0.204$, and $p = 0.215$, respectively).

measures ANOVA with respondents' preferred amount of AI involvement in each of the five policy cycle phases (agenda-setting, policy formulation, policy decision-making, policy implementation, and policy evaluation) as within-subjects factor and the information availability manipulation (*'no info'* vs. *'info'* condition) as between-subjects factor was conducted. The results of this analysis are provided in Table 7 and visualized in Fig. 5.

First of all, Fig. 5 demonstrates that—regardless of the phase being considered and irrespective of the information availability condition—respondents consistently preferred humans to have more weight than AI in public policy processes, which signals that they prefer humans to remain in control (i.e., more than 50% decisional weight). However, when comparing the different phases with each other, it was found that respondents prefer AI to have the most weight during the policy evaluation phase, followed by the policy implementation phase, the policy formulation phase, the agenda-setting phase, and finally the policy decision-making phase. The differences between the five phases all reached statistical significance (all *ps* < 0.001), with exception of the difference between the policy formulation and the policy implementation phase ($p = 0.777$; see Appendix H for more details on the pairwise comparisons). Moreover, for each of these five phases, the amount of weight that respondents prefer AI to have was always significantly higher in the *'info'* condition than in the *'no info'* condition (all *ps* $<$ 0.001; see Appendix I for details on the pairwise comparisons).

5. Discussion

In recent years, the rapid advancement of AI has begun to significantly transform the public sector. Although emerging research has explored public servants' attitudes toward AI involvement (e.g., Ahn & Chen, 2022; Haesevoets et al., 2025; Nagtegaal, 2021; Ruvalcaba-Gomez & Cifuentes-Faura, 2023), important questions remain about how they specifically perceive this ongoing transformation; and under which conditions they are most (and least) willing to accept it. Given their pivotal role in the implementation and adoption of such emerging technologies (Ahn & Chen, 2022; van Noordt & Misuraca, 2022), the present study seeks to address these gaps by experimentally investigating UK public servants' ($N = 801$) attitudes toward AI integration, focusing on three key dimensions: (1) the level of AI involvement, (2) the specific phase of the policy cycle in which AI is introduced, and (3) the availability of information about AI's potential applications.

5.1. Reflection on the main findings

The overall objective of the present study was thus to gain deeper insights into public servants' attitudes toward AI involvement in public policymaking processes. While several recent studies have suggested a *'generally'* positive attitude toward AI among public servants (e.g., Ahn & Chen, 2022; Distor et al., 2021; Ruvalcaba-Gomez & Cifuentes-Faura, 2023), we found a more skeptical stance. Specifically, and consistent

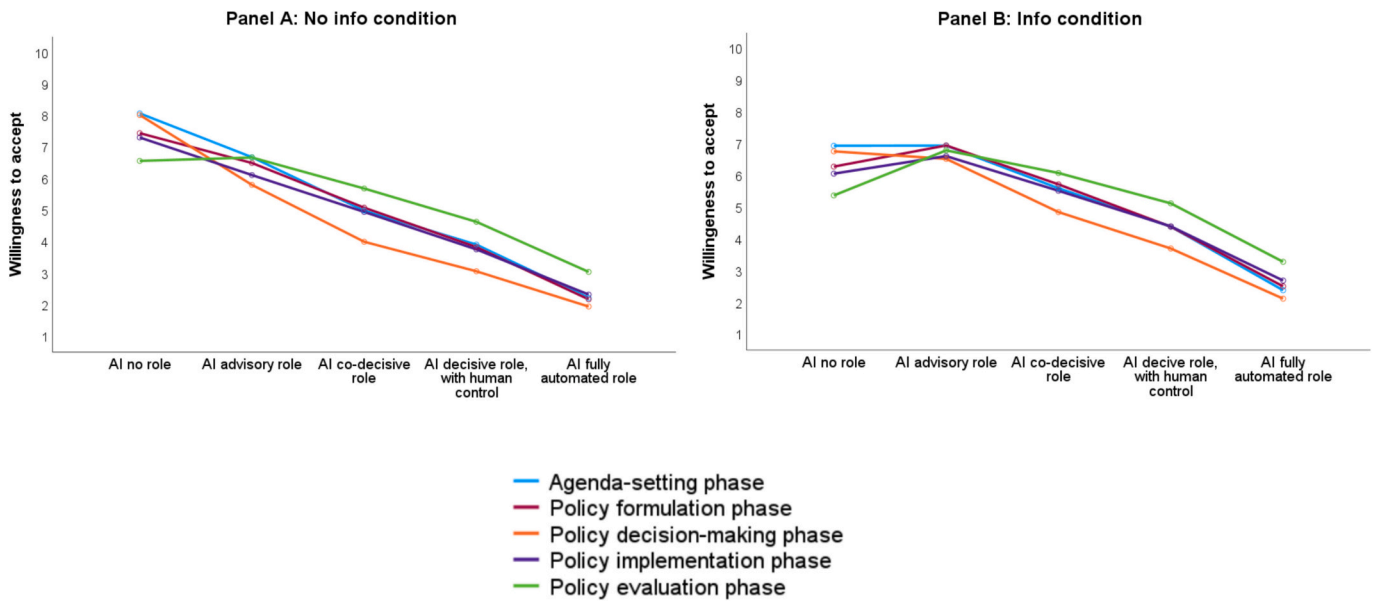

Fig. 3. Respondents' willingness to accept the different *role* configurations (error bars reflect standard errors).

Table 6
Evaluation of the *weight* configurations: Results of the repeated-measures ANOVA with 'Policy Cycle Phases' and 'Weight Configurations' as within-subject variables and 'Information Availability Condition' as between-subjects variable.

Effects	df	*F*	*p*	partial η^2
Information Availability Condition	1, 799	2.79	0.095	0.003
Policy Cycle Phases	4, 796	78.38	< 0.001	0.283
Weight Configurations	4, 796	943.11	< 0.001	0.826
Phases × Condition	4, 796	7.54	< 0.001	0.037
Weight Configurations × Condition	4, 796	22.04	< 0.001	0.100
Phases × Weight Configurations	16, 784	28.27	< 0.001	0.366
Phases × Weight Configurations × Condition	16, 784	2.50	< 0.001	0.049

Note. Similar results were obtained when the standardized score of gender, age, education level, seniority, and employer type were included as covariates in the analysis (i.e., all effects that were significant remained significant, whereas the non-significant main effect of 'Condition' remained non-significant; $p = 0.194$).

with the recent findings of Haesevoets et al. (2025), our detailed examination shows that UK public servants actually prefer AI to remain in an advisory role, ideally exerting no more than 25% influence in policymaking. These results suggest that, at least in the UK context, public servants seem more cautious and reserved about the integration of AI into government operations than the public sector literature has typically assumed. Notably, our findings also align with prior research in the private sector, which found that private sector workers also strongly oppose arrangements in which AI takes the lead (e.g., De Cremer & McGuire, 2022; Haesevoets et al., 2021).

Our *first hypothesis* proposed that public servants would express the most positive attitudes toward increasing levels of AI involvement in agenda-setting and policy evaluation, intermediate attitudes during policy formulation and policy implementation, and the least positive attitudes in policy decision-making. The results largely support this expectation. Specifically, across our different outcome measures, we consistently found that attitudes toward AI were least positive for the policy decision-making phase, and most positive for the policy evaluation phase. Public servants thus appear more comfortable with AI in analytical or assessment-oriented contexts, where tasks are perceived as more technical and data-driven, and where AI can be seen as an impartial tool that enhances efficiency and objectivity. Conversely, during policy decision-making, where discretion, accountability, and the need for human judgment are most salient, AI involvement elicited stronger reservations. Interestingly, however, the anticipated high positivity during the agenda-setting phase was not supported: attitudes toward AI at this stage were more moderate, suggesting that public servants may view early-stage agenda formation as requiring human sensemaking and political sensitivity that cannot easily be replicated by automated systems. Together, these findings indicate that perceptions of AI suitability indeed vary substantially across policy cycle phases, reinforcing the need for a fine-grained understanding of where and how AI can best support the policymaking process.

Our *second hypothesis* stated that public servants would express more positive attitudes toward extensive AI involvement when information about AI's potential applications and functionality is provided, compared to when no such information is given. This hypothesis was fully supported. As expected, respondents in the *'info'* condition consistently reported more favorable evaluations of AI involvement than those in the *'no info'* condition. This suggests that the provision of clear, concrete information about AI's possible uses can significantly enhance perceptions of AI. Even though the information manipulation in the present study was relatively limited, its effect was substantial, indicating that communication strategies and knowledge dissemination play a crucial role in shaping public servants' openness to AI integration in governance contexts.

5.2. Implications for research and practice

The present findings offer several important implications for research and practice. A first consideration for research relates to the interchangeability of the role and weight configurations that were studied in our paper. Although the *weight* configurations focus on abstract degrees of AI involvement and the *role* configurations detail more specific AI functions, our analyses show that respondents did not substantially differentiate between these two configuration types in their evaluations. This similarity suggests that considering the numerical degree of AI involvement (weight configurations) or its specific role (role configurations), respondents' preferences were consistent across

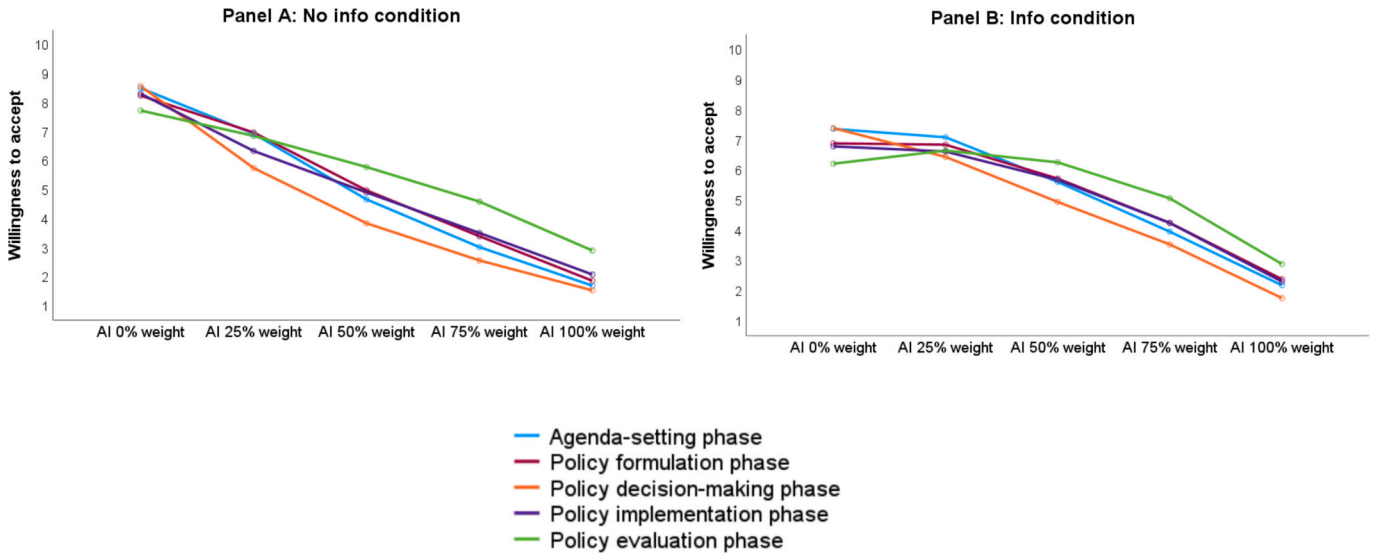

Fig. 4. Respondents' willingness to accept the different *weight* configurations (error bars reflect standard errors).

Table 7
Preferred amount of AI involvement: Results of the repeated-measures ANOVA with 'Policy Cycle Phases' as within-subject variable and 'Information Availability Condition' as between-subjects variable.

Effects	df	*F*	*p*	partial η^2
Information Availability Condition	1, 799	53.90	< 0.001	0.063
Policy Cycle Phases	4, 796	133.14	< 0.001	0.401
Phases × Condition	4, 796	0.75	0.559	0.004

Note. The inclusion of the standardized covariates (gender, age, education level, seniority, and employer type) did again not alter the results (main effect of 'Condition': $F(1, 794) = 51.25$, $p < 0.001$, partial $\eta^2 = 0.061$; main effect of 'Phases': $F(4, 791) = 133.42$, $p < 0.001$, partial $\eta^2 = 0.403$; interaction term: $F(4, 791) = 1.15$, $p = 0.334$, partial $\eta^2 = 0.006$).

both types of configurations. This interchangeability implies that researchers can effectively use either method to gauge peoples' attitudes toward AI integration, without concern that they are measuring fundamentally different constructs.

Secondly, on a more practical level, the notable disparity observed between our two information availability conditions indicates that the skepticism that we observed among public servants may actually stem (at least in part) from a lack of understanding or familiarity with AI technologies and its potential benefits (cf. Horowitz et al., 2024). Targeted 'educational' programs designed to bridge this knowledge gap can play a pivotal role in enhancing the readiness of public servants to accept and embrace the implementation of AI applications in public policy processes. Educating public servants about AI's capabilities and potential roles may indeed be a critical factor in fostering acceptance and positive attitudes toward AI integration (see Phuangthuean & Nuansang, 2024; also see Huang et al., 2024).

Importantly, however, effective educational strategies should not only focus on the technical aspects of AI but, more crucially, emphasize its concrete contributions to public sector processes. These efforts should demonstrate how AI can practically enhance decision-making, efficiency, and service delivery. Additionally, educational initiatives should be ongoing and adaptable, responding not only to technological advancements but also to the evolving needs of the public sector. By maintaining a consistent focus on the tangible benefits that AI can bring, governments can empower their workforce through continuous learning and development opportunities, allowing them to fully harness AI's 'transformative potential' (see Allioui & Mourdi, 2023; Kawtar & Khadija, 2024).

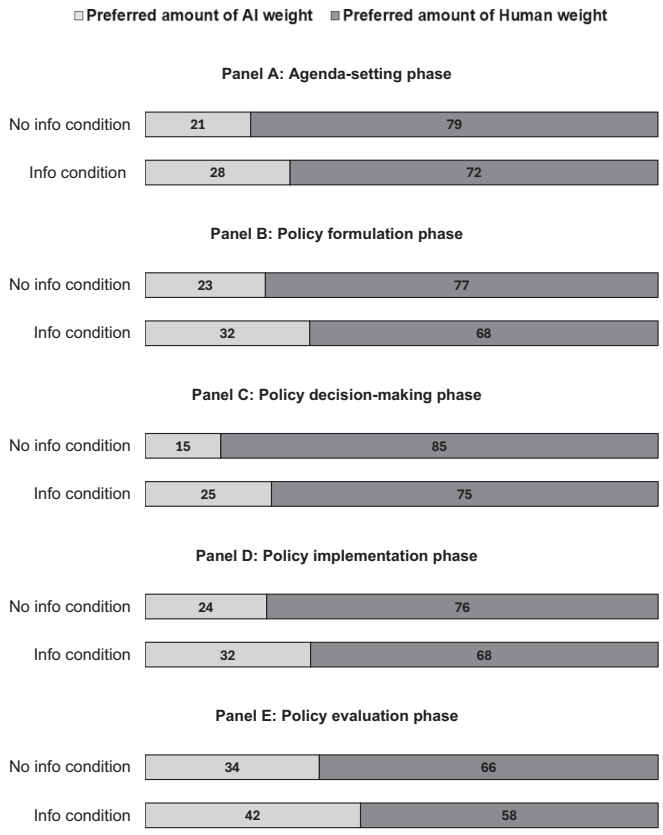

Fig. 5. Respondents' preferred amount of human and AI involvement.

Moreover, the observed variation in public servants' attitudes across different policy cycle phases suggests a need for more tailored approaches to AI integration. Specifically, the way AI is integrated into each phase should reflect the unique requirements and sensitivities of that phase. For instance, during critical decision-making phases, where human judgment is deemed indispensable, AI's role may need to be carefully circumscribed to advisory capacities. This means that AI should be used to support and inform human decision-makers rather than replace them (cf. Haesevoets et al., 2021, 2024,; De Cremer & McGuire, 2022). AI can provide data analysis, predictive modeling, and

scenario simulations, but the final decision should be made by human agents. Conversely, in phases focused on data-driven evaluation and implementation, AI may play a more substantial role. These latter stages often involve analyzing large datasets, monitoring outcomes, and optimizing processes, tasks well-suited to AI's strengths.

Given the observed differences across the policymaking phases, a gradual approach to AI implementation seems advisable. AI should first be introduced in the less contentious phases, such as policy evaluation, where public servants are relatively more open to its use. Demonstrating AI's usefulness in these phases can build confidence in its capabilities and create a foundation for gradually expanding AI into other policymaking stage. By successfully showcasing AI's effectiveness and reliability in outcome evaluation, public servants can build confidence in the added value of AI technologies. Over time, success in this phase could then serve as a catalyst for expanding AI's role into other phases of the policy cycle. Indeed, as public servants witness the tangible benefits and improvements brought about by AI in the evaluation phase, they may become more open to incorporating AI into other stages as well; although (full) openness to AI adoption in the critical decision-making phrase might never occur. Implementing AI in such a 'gradual' of 'phased' manner can help mitigate resistance and foster smoother integration across the policymaking cycle, ultimately enhancing the efficiency and effectiveness of public sector operations.

Finally, AI implementation should also incorporate mechanisms for continuous feedback and adaptability. Beyond initial screening, it is essential to gather ongoing input from public servants as AI is introduced and evolves within policy processes. As AI applications and attitudes toward them change over time, continuous feedback mechanisms can ensure that AI remains aligned with the needs and expectations of public servants. This iterative approach allows for necessary adjustments and fosters greater long-term acceptance of AI in policymaking.

5.3. Limitations and future research directions

Although the present findings advance several new insights into public servants' attitudes toward AI involvement in governmental processes, our study is not without limitations. A first methodological consideration is that we did not pre-register our hypotheses prior to conducting the study, as the research was conceptualized as an exploratory study into the patterns in AI attitudes across different dimensions rather than as a test of a specific effect. Another methodological consideration concerns the design of our information availability manipulation. The *'info'* condition necessarily included longer vignette texts than the *'no info'* condition, as it provided additional information about potential AI applications. Although this difference directly reflects the treatment itself, variations in text length may affect cognitive engagement independently of content (Krosnick, 1991; Tourangeau et al., 2000). We deliberately chose not to add filler text to the control condition, as doing so would change the nature of the manipulation from 'info vs. no info' to 'relevant vs. irrelevant information', which deviates from the theoretical rationale. Nevertheless, future research in this domain could consider controlling for text length to further isolate the effect of information provision.

Relatedly, the content of the information provided in the *'info'* condition emphasized AI-related opportunities and benefits rather than potential risks. This positive framing may have introduced a 'positivity bias' (Unkelbach et al., 2020), potentially portraying AI in an overly favorable light. Since we did not systematically vary the valence of the information (i.e., positive vs. negative framing), our study does not fully address how different framings might shape attitudes among public servants. Prior research has shown that framing effects can significantly influence AI perceptions (e.g., Banks & Koban, 2021; Choi, 2024; Kim & Song, 2023; Nam & Bell, 2024; Nguyen & Hekman, 2022), and future studies should systematically manipulate the tone and content of information.

The present study also faces potential limitations related to the recruitment and composition of the sample. Respondents were recruited via Prolific, an online research platform providing access to a diverse participant pool. However, participants are self-selected and may differ from the broader population of public servants in terms of digital literacy, familiarity with online surveys, or interest in AI, introducing potential selection bias. In this vein, it should also be noted that our sample is not fully representative of the UK public sector workforce, with a slight overrepresentation of younger and female respondents. Moreover, although some minor differences in age and seniority were observed between the two information availability conditions (see descriptive details in Appendix A), the subgroup analyses indicate that these differences had no impact on the relative ordering of policy phases or on the effect of information provision (illustrated in Appendix E). Taken together, these findings suggest that small demographic imbalances do not meaningfully affect the main conclusions of the study.

The study's geographical scope presents another limitation. The present research was conducted exclusively among respondents from the UK, and the specific socio-cultural, political, and institutional characteristics of this context may limit the generalizability of the findings to other countries or regions. Extending this research to additional national contexts would allow for a more systematic assessment of whether the observed patterns in attitudes toward AI adoption among public servants hold across diverse cultural and institutional settings. Comparative studies, in turn, could yield a more comprehensive understanding of the contextual factors influencing attitudes toward AI integration in public policy processes. This represents an essential step toward developing nuanced strategies and policies that address the diverse needs and challenges faced by public sectors globally in adopting AI technologies. In addition to these cross-country considerations, our study captures attitudes at a single point in time, which may not reflect how perceptions of AI evolve. Future research could also employ longitudinal designs to monitor changes in acceptance, concerns, and the role of AI over time, providing insights into the sustainability and long-term impacts of AI integration in public policy processes.

Another important consideration concerns the operationalization of AI in this study. We conceptualized AI as a broad construct and did not differentiate between specific types or applications. Rather than focusing on particular implementations, AI was treated as an umbrella term encompassing various technologies and functions. Future research could extend these findings by investigating how public servants' attitudes vary across specific AI types or applications in different administrative and policy contexts. For instance, attitudes may differ depending on whether AI systems are rule-based or data-driven, as the latter may raise stronger concerns about transparency, fairness, and the so-called 'black box' issue (Adadi & Berrada, 2018). Similarly, citizen-facing applications (e.g., automated benefit assessments) may elicit stronger reactions than internal analytical tools (e.g., predictive models for policy design). Exploring such distinctions could offer further, more fine-grained insights into the conditions under which AI usage is perceived acceptable.

While our study focused on how public servants' AI adoption attitudes are shaped by the level of AI involvement, the policy cycle stage, and information availability, we did not directly measure underlying values, beliefs, or prior behaviors. Nonetheless, it is likely that such factors play an important role in shaping individuals' attitudes toward technological innovations. Professional norms, organizational culture, and prior exposure to technology may interact with contextual and informational conditions to influence perceptions of AI. For instance, beliefs about fairness, accountability, or motivations related to public service could affect whether public servants are more receptive to AI in certain policy stages or when provided with specific information. Future research could extend our experimental design by explicitly incorporating measures of individual values, beliefs, and prior experiences. Doing so would allow for a deeper understanding of the mechanisms through which these factors influence AI acceptance and help explain why some public servants are more supportive of AI in particular

governance contexts than others.

A further limitation lies in our reliance on the policy cycle framework. While this framework provides a structured approach to understanding how AI can be integrated across different stages of policymaking, it is an idealized model that may not fully capture the complexity and non-linearity of real-world policy work. Public officials often engage in task-oriented activities such as tracking emerging issues, developing policy tools, or responding to immediate challenges, which may not follow the linear progression suggested by the policy cycle. Nonetheless, the framework remains useful for identifying key stages and exploring the extent to which AI involvement might be accepted at each stage. Future research could complement this framework by investigating alternative approaches that better reflect practical policymaking realities and task-based activities.

In addition to future research directions arising from study-specific limitations, several broader avenues emerge that build directly on the findings and implications of this work. First, decision-making and delegation in AI-enhanced public organizations warrant deeper investigation. Public managers frequently face high-stakes and ambiguous decisions. With AI, they now have the option to delegate such decisions to automated systems, which can shift responsibility and affect organizational dynamics. In this vein, future studies could explore potential misalignments between managerial preferences to delegate ambiguous decisions to AI and public employees' expectations regarding who should make such decisions. Secondly, leadership and workforce development in AI-driven public service environments also represent a key area for further exploration. As AI reshapes work processes, human roles may shift toward interpersonal, ethical, and collaborative competencies. Future research could examine how leadership practices in public administration adapt to these changes, how employees' skills and capabilities evolve, and how public organizations can support effective human-AI collaboration while maintaining service quality and organizational mission. Thirdly, trust in human-AI interactions within public sector organizations also warrants closer attention. Understanding the factors that foster or undermine trust, as well as strategies to maintain or restore trust following AI-related failures, is critical for sustainable AI adoption. Taken together, these research directions provide a comprehensive yet targeted agenda for examining human-AI relationships in public organizations. By focusing on delegation, leadership, workforce adaptation, and trust, future studies can generate actionable insights to support responsible, effective, and human-centered AI integration in the public sector.

6. Conclusion

The present study offers novel insights into UK public servants' attitudes toward AI adoption within governmental operations, revealing a persistent skepticism toward more extensive forms of AI integration, particularly when AI moves beyond providing support or advice. This cautious stance was most pronounced for the decision-making phase of the policy cycle and least evident in the evaluation phase, underscoring that receptivity to AI indeed varies across different stages of policymaking. Furthermore, our findings highlight the critical importance of information availability in shaping AI adoption attitudes, suggesting that greater transparency and understanding of how AI integration could take shape, can help mitigate concerns about automation and control. From a practical perspective, these insights call for more tailored AI implementation strategies that are sensitive to the unique demands and risk perceptions associated with each phase of the policy cycle. Policymakers should also invest in targeted educational and training initiatives to bridge existing knowledge gaps and build informed confidence among public servants. By addressing these considerations, governments can navigate the complexities of AI adoption more effectively, fostering more balanced and contextually informed approaches to technology integration. Ultimately, this can enhance alignment between AI-driven innovations and the values, expectations, and professional judgment of public servants, thereby supporting a legitimate and sustainable digital transformation within the public sector.

CRediT authorship contribution statement

Tessa Haesevoets: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Bram Verschuere:** Writing – review & editing, Funding acquisition. **Alain Van Hiel:** Writing – review & editing, Conceptualization. **Arne Roets:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization.

Informed consent

This study was conducted in accordance with the Research Code of Ethics of the Faculty of Economics and Business Administration of Ghent University. All participants provided their informed consent.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.giq.2026.102134.

Data availability

The data and data analysis scripts of our study are made publicly available and can be accessed through Open Science Framework: https://osf.io/swk5d/overview.

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