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Support for AI in Public Administration: A Comparative Study of the United Kingdom and Japan

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ABSTRACT

As public administrations increasingly adopt AI, understanding citizens' attitudes toward algorithmic decision-making has become important for maintaining legitimacy and public trust. We find that citizens in both the UK and Japan are relatively open to AI handling routine administrative functions, but support declines when AI is associated with more complex or discretionary decisions. Individuals who perceive AI as beneficial and who report higher levels of digital self-efficacy are significantly more supportive of AI in public administration, while fear of AI reduces support. Trust in government consistently predicts acceptance of administrative AI, whereas generalized social trust plays a weaker role. Japan shows higher baseline support but also heightened caution, while attitudes in the UK are more ideologically divided. Public acceptance of AI in government depends not only on institutional trust but also on broader social perceptions of the technology and the perceived complexity of the tasks it performs.

KEYWORDS

AI; public administration; UK; Japan; trust

Introduction

The integration of artificial intelligence (AI) into public administration promises to transform public services and bureaucratic processes. In both the United Kingdom and Japan, public agencies have been experimenting with AI tools to improve efficiency, from chatbots assisting with citizen inquiries to machine-learning algorithms aiding decision-making in welfare, policing, and beyond. Such innovations are often framed within broader digital governance agendas, such as the UK's national AI strategy and Japan's "Society 5.0" vision. These portray AI as a means to enhance public sector effectiveness and address societal challenges (Narvaez Rojas et al., 2021). Yet the success of these initiatives depends not only on technical feasibility but also on public acceptance. Public opinion plays a pivotal role in legitimizing the use of AI in public administration, as citizens' trust and support can shape preferences for AI regulation, and may influence policymakers' willingness to deploy automated systems and shape the outcomes of implementation (Bullock et al., 2025; Madan & Ashok, 2023).

Existing research highlights a duality in public perceptions of AI in governance. On the one hand, there is optimism that AI can make public services more

efficient, impartial and responsive, potentially creating public value through faster processing of routine tasks and data-driven policy insights (Engin & Treleaven, 2019; European Commission, 2020; Janssen & Kuk, 2016). On the other hand, significant concerns persist about transparency, fairness and accountability when algorithms assist or replace human public servants (Busuioic, 2021). Public controversies, from algorithmic bias in decision systems to notable failures like the UK's 2020 exam grading algorithm scandal, have underscored how negative opinion can swiftly erode confidence in public administration AI applications (Tieleman, 2025). In Japan, although robotics and automation enjoy a generally positive cultural niche, surveys reveal considerable anxiety over AI's societal impacts, including fears of job displacement and misuse of data (Morikawa, 2017). These contrasting currents in public sentiment make it important to systematically analyze how the public in both countries views the use of AI in administrative contexts.

This article investigates public opinion toward AI in public administration in the UK and Japan through original survey data. We focus on three measures of support: the level of support for AI handling simple administrative tasks; support for AI handling complex decision-making tasks; and overall support for AI in

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public administration. By examining these dependent variables, alongside a number of key independent variables, we aim to identify which factors drive public support or opposition. Specifically, we consider demographic attributes (age, gender and university education), interpersonal and political attitudes (trust in government, trust in others, general risk-taking propensity and left–right political ideology), and AI-specific perceptions (fear of AI, self-assessed knowledge of AI and belief in AI’s benefits). The analysis is grounded in frameworks of digital governance and public sector effectiveness, yet remains centered on public opinion: how citizens’ views might influence and be influenced by the integration of AI into public administration.

In the following sections, we first review the context of AI in public administration, highlighting potential benefits and challenges as discussed in recent literature. We then explore how public opinion can affect decisions within the public sector, linking citizen attitudes to bureaucratic adoption and legitimacy of governance. After a brief note on our data and methodology, we present the findings of our survey analysis. We then discuss the implications of these findings, comparing the UK and Japanese contexts and outlining perspectives for public administrators to improve public support for AI initiatives. Finally, we conclude with a summary of insights and considerations for future policy and research.

AI and public administration

Governments worldwide are accelerating the adoption of artificial intelligence (AI) to enhance public sector performance. In public administration, AI encompasses technologies such as machine learning, natural language processing, and robotics that support or partially replace tasks traditionally performed by civil servants. In the United Kingdom, local authorities have piloted algorithmic systems for benefit assessments and service allocation, while chatbots increasingly handle routine citizen inquiries (Vogl et al., 2020). In Japan, AI tools have been introduced to support elderly care planning and disaster response, advancing the government’s vision of a “super smart society” under Society 5.0 (Narvaez Rojas et al., 2021). These initiatives are motivated by the expectation that AI can improve efficiency through faster processing and cost reduction, enhance effectiveness through data-driven accuracy and service personalization, and potentially increase objectivity by mitigating human bias (Janssen & Kuk, 2016; Young et al., 2019).

At the same time, the integration of AI into public administration raises substantial normative and institutional challenges. When algorithms shape decisions

about welfare eligibility or service prioritization, an “accountability gap” may emerge in which responsibility for errors or unfair outcomes becomes difficult to assign (Busuioc, 2021). Moreover, complex machine learning systems often operate as “black boxes,” limiting transparency and potentially eroding public trust (Grimmelikhuisen, 2023; Schiff et al., 2022). Fairness concerns are equally salient: if training data embed historical biases, AI systems may reproduce or amplify inequalities, thereby undermining governmental legitimacy (Barocas & Selbst, 2016; Mitchell et al., 2021). The withdrawal of the UK’s exam grading algorithm following public criticism illustrates how quickly governments may be compelled to reverse course when AI systems are perceived as violating egalitarian norms (Tieleman, 2025). AI implementation thus unfolds within a persistent tension between performance enhancement and the preservation of democratic values.

From a governance perspective, the acceptance of AI in public administration is intimately connected to questions of legitimacy and public value. Public administration scholars distinguish between different dimensions of legitimacy: input legitimacy (the perception that decision processes are participatory and reflect citizens’ voice), throughput legitimacy (the perception that processes are fair, transparent and accountable), and output legitimacy (the perception that the outcomes or services delivered are effective; see Schmidt, 2013). AI has a complex profile across these dimensions. On the one hand, if AI improves outputs, such as through faster services or more accurate decisions, it can bolster output legitimacy, making citizens feel the government is effective. Indeed, recent research suggests that, with respect to the perceived legitimacy of outputs, particularly in terms of efficiency and performance, citizens tend to place nearly the same level of trust in AI systems as they do in human experts (Haesevoets et al., 2024). On the other hand, AI scores poorly on input and throughput legitimacy in the public eye: people do not elect algorithms, nor do algorithms deliberate in public forums, and an AI’s decision process lacks the transparent, explainable qualities that people expect from public institutions (Lee, 2018; Starke & Lünich, 2020).

Digital governance frameworks increasingly call for a human-centered approach to AI in the public sector; one that embeds ethical guidelines, stakeholder engagement and oversight mechanisms. Both the UK and Japan have developed AI governance principles (such as the UK’s Office for AI guidance and Japan’s AI Utilization Principles) that emphasize transparency, accountability and the importance of maintaining human control over AI-assisted decisions. The underlying rationale is that sustaining public trust requires

demonstrating that AI is used as a tool to assist, rather than replace, human public servants, especially in complex or value-sensitive contexts. Early empirical evidence supports this approach: citizens are far more comfortable with AI systems that operate in an advisory capacity with final decisions made by humans, rather than with fully autonomous AI decision-makers. For example, surveys in the UK have shown a strong public preference for “human-in-the-loop” models, where an AI might analyze information or suggest a recommendation, but a human official exercises judgment in the final decision (Haesevoets et al., 2024). Similarly, in a Japanese context, explicitly assuring people that humans remain involved in AI-assisted decision processes significantly increases their trust in the system’s outcomes (Aoki, 2021).

However, articulating high-level principles for AI governance is not sufficient (Mittelstadt, 2019). Recent advances in AI have fundamentally altered the scope and nature of human involvement. Earlier discussions assumed that AI would be confined largely to routine administrative tasks and that the implementation of complex systems would remain technically and organizationally challenging (Janssen & Kuk, 2016). Today, however, machine learning systems can address highly complex problems through data-driven prediction, in some cases outperforming trained human experts (Kleinberg et al., 2018). Yet these gains in predictive performance come with diminished interpretability: understanding and explaining why certain outputs are produced remains difficult, and simply publishing source code does not by itself guarantee accountability. In this context, rule-based decision systems—grounded in predefined human knowledge and explicitly programmed rules—are often perceived as more transparent and procedurally fair, and therefore more readily accepted (Janssen et al., 2020; Wang et al., 2023). At the same time, increasingly sophisticated AI systems require skilled personnel capable of designing, implementing, and overseeing them (Dingelstad et al., 2022), while raising concerns about the risk of automation bias, whereby humans defer uncritically to algorithmic judgments (Alon-Barkat & Busuioc, 2023; Giest & Klievink, 2022). Determining when and how AI should be deployed is therefore inherently context-dependent. Effective integration demands careful institutional design tailored to specific purposes and governance settings (Kasirzadeh & Gabriel, 2025; Wenzelburger et al., 2024).

As such, AI offers appealing opportunities for public administration improvements, but its adoption is accompanied by non-technical prerequisites: robust accountability frameworks, transparency measures

(such as explainable AI outputs and open communication), and careful alignment with public values and expectations (Mosqueira-Rey et al., 2022; Schmitz & Bryson, 2025). Without public buy-in, even technically successful AI projects can falter due to legitimacy deficits. This dynamic underlines the importance of understanding public opinion as a key factor in the relationship between AI innovations and actual administrative decision-making practice.

Public opinion and decision-making in public administration

Public opinion can significantly shape the trajectory of technological adoption in government. In democratic societies, the legitimacy of administrative decisions, including the decision to deploy AI systems, often hinges on public acceptance, or at least public acquiescence. Elected officials and agency leaders are unlikely to embrace AI tools in sensitive areas if they anticipate voter backlash or a loss of public trust in institutions. Therefore, understanding citizens’ attitudes toward AI is key for public administrators who must balance innovation with maintaining legitimacy and public confidence. The UK and Japan provide illustrative contexts in this regard, as both have strong bureaucratic institutions yet different political cultures in terms of public engagement and baseline trust in government.

One of the ways public opinion feeds into public administration decisions is through the mediation of political oversight. If the public expresses high levels of concern about AI, such as worries about privacy violations, errors, or job impacts, politicians and oversight bodies may act cautiously, imposing strict regulations or even halting AI initiatives. Empirically, there have been cases where public skepticism delayed or reshaped government AI projects. For example, controversy in the Netherlands over automated welfare fraud detection systems led to legal challenges and program suspensions amid public concern about fairness (Van Bekkum & Borgesius, 2021); and in the UK, as noted, the outcry over an algorithmic grading system prompted its rapid withdrawal (Tieleman, 2025). In Japan, while the government is eager to introduce AI programs (such as health data management) to improve healthcare quality, stakeholders share concerns about privacy and data management, issues surrounding accountability, and the potential loss of the “human touch” in healthcare (see Katirai et al., 2023). In both countries, public servants are aware that conspicuous failures of AI, or a perception that bureaucrats are deploying “unfeeling” machines to make decisions about citizens, can quickly

erode trust in the agency and spark political intervention.

Public opinion does not only operate as a veto or constraint; it can also provide a mandate or impetus for innovation when positive. If citizens broadly support the use of AI in certain government functions (such as to improve traffic management or reduce administrative red tape) public administrators have greater latitude and political backing to implement those technologies. The alignment of an innovation with public preferences can result in a virtuous circle: initial support leads to pilot programs whose successes further bolster public approval, creating an environment for scaled adoption. For instance, indications in the UK are that the public is relatively comfortable with AI being used in “back-office” government tasks or in domains like traffic control and resource allocation, where the personal stakes are lower and the potential convenience is high. Knowing this, agencies might prioritize AI projects in these areas as low-risk, high-benefit endeavors that are unlikely to trigger controversy. In Japan, there appears to be public enthusiasm for AI and robotics addressing the challenges of an aging population, such as AI-assisted caregiving or administrative support in social services, due to widespread recognition of labor shortages in the public sector. Public administrators, aware of these opinions, may thus feel a mandate to pursue AI solutions in eldercare, healthcare administration and similar areas where the technology is seen as meeting a genuine public need (Nakamura, 2022). At the same time, it is important to recognize the feedback loop: administrative decisions and communication strategies can actively shape public opinion, not just respond to it.

Public administration has tools at its disposal, such as transparency initiatives, citizen education programs and participatory forums, that can influence how citizens perceive AI. If an agency proactively engages the public by explaining how an AI system works, what benefits it brings and what safeguards are in place, this can mitigate fears and build trust (Androusoy et al., 2019). For example, experimental trials in the UK found that while initial public reactions to AI chatbots in government services were marked by skepticism, providing clear information about the chatbot’s purpose, capabilities, and limitations significantly improved users’ trust and willingness to engage with the service (Behavioural Insights Team & Nesta, 2024). Experimental evidence from Japan shows that public trust in government chatbots increases when authorities clearly communicate their beneficial purposes, such as standardizing response quality and enabling rapid service delivery (Aoki, 2020). Research corroborates this

approach: when citizens feel informed about an AI system and know that humans are overseeing its operations, they report higher levels of trust in the technology’s use (Aoki, 2021; Horvath et al., 2023). This suggests that administrative transparency and engagement can convert what might initially be skepticism into more supportive attitudes over time.

An important link between public opinion and bureaucratic decision-making is the concept of trust. Trust in government acts as a reservoir of goodwill that shapes how citizens interpret new administrative initiatives. Technological progress can produce both desirable and undesirable outcomes, allowing individuals to reap benefits while simultaneously bearing certain costs (Krarup & Horst, 2023). Trust plays a key role in enabling people to accept new technologies despite their awareness of potential negative consequences (Robles & Mallinson, 2025). If citizens trust that their government is competent and has their best interests at heart, they may be more willing to give the benefit of the doubt to an AI implementation and wait to see results. In contrast, if trust in government is low, people may interpret the introduction of AI as yet another move by unaccountable officials or technocrats, and react negatively. The UK has in recent years experienced fluctuating trust in public institutions, and some analyses have observed that the success or failure of digital reforms often depends on these trust dynamics (OECD, 2024; Parliamentary Office of Science and Technology, 2025). Japan historically has had relatively high trust in its bureaucracy but also a cautious public when it comes to new technologies; this dynamic means that Japanese administrators benefit from an initial trust buffer, but they must still carefully manage AI deployments to avoid undermining that goodwill.

Beyond trust, a growing body of research highlights additional attitudinal factors that shape public reactions to the use of AI in government. Political ideology is one such factor: because partisanship constitutes a central component of social identity, ideological orientations may influence how individuals evaluate technologies that claim to generate public value. Yet the evidence remains inconclusive as to whether AI adoption is structured along clear partisan lines (Gur et al., 2024; Schiff et al., 2022, 2025). Some studies find that right-leaning individuals, who emphasize economic freedom and market dynamism, are more supportive of AI adoption, while others suggest that left-leaning individuals, who prioritize social progress and innovation, are similarly receptive. Another factor is risk tolerance: citizens who are more comfortable taking risks may be more open to their government trying new, unproven technologies, whereas risk-averse individuals might prefer the status

quo of human officials. Together, ideology and risk orientation provide essential insight into the broader social context shaping AI adoption in the public sector (Wenzelburger et al., 2024).

Public attitudes toward AI are not necessarily one-dimensional. Individuals may support the use of data-driven algorithms when they deliver accurate predictions and offer clear convenience. At the same time, research suggests that people often privilege their own judgment or that of other humans over algorithmic recommendations, even when the latter are demonstrably more accurate (Dietvorst et al., 2015). Concerns about accountability further complicate acceptance: when responsibility for AI-driven decisions is unclear, citizens may become skeptical of algorithmic authority. Yet empirical evidence also indicates that the aversion to algorithms is conditional rather than absolute. When AI systems are perceived as functioning effectively and producing reliable outcomes, public resistance tends to be relatively limited (Kennedy et al., 2022; König et al., 2022).

Public opinion serves as both a barometer and a steering force for AI adoption in public administration. Leaders in public administration need to consider public sentiment and engage with it: supportive opinion can be harnessed to drive beneficial innovation, while skeptical opinion must be managed through transparency, engagement, and adjustments to implementation strategies. This interplay sets the stage for our empirical analysis, where we directly measure and analyze public support for AI in government in the UK and Japan and assess how various factors, from trust to fear, condition that support. Understanding these relationships will inform how public administrations might strategize the introduction of AI in ways that are responsive to citizen attitudes.

Data and Methodology

Our data were collected via online surveys in the United Kingdom and Japan. In the United Kingdom, this was done via the YouGov online panel in November 2024 and in the same month in Japan through the Rakuten Insight panel. Full anonymized replication data and code are available from the Harvard Dataverse, at <https://doi.org/10.7910/DVN/AWHYKA>. Our total population for the United Kingdom was 1322 respondents and for Japan 2611 respondents. When we restricted the samples to those who had completed all of the questions used in the analysis successfully, this gave us 987 respondents in the UK and 2157 respondents in Japan. Participants were allocated by gender and age in each country; however, it should be noted

that the upper age range in the Japan sample is more limited. In addition, because the data were collected via online surveys, respondents may be relatively more comfortable with digital technologies.

We focus on two outcome variables. After being presented with the prompt, “Thinking about the advancement of artificial intelligence (AI) over the next few years, to what extent would you support or oppose the following uses of AI in politics?,” respondents were asked to rate two statements: first, “AI performing simple routine tasks in public administration,” and then, “AI performing complex tasks in public administration.” The respondents were asked to rate these on a five-point scale with the lower value of 1 being “Do not support at all” and 5 means “Support completely.” The questions are similar to those asked by König (2023), although his primary focus is on the use of AI in more intrusive forms of decision-making, and König treats simple and complex administrative tasks jointly as a single administrative context. Nevertheless, the data clearly show that public acceptance differs substantially between routine tasks and more complex ones, with evaluations of complex administrative tasks resembling attitudes toward AI-assisted political decision-making (König, 2023, Figure 1). Consistent with this pattern, Table 1 demonstrates that in our data, too, the distinction between simple routine tasks and complex tasks is pronounced in both Japan and the United Kingdom.

König treats these tasks as a single category, yet public acceptance may vary substantially between the use of AI for simple routine tasks and for more complex functions. Highly personalized and complex services, for example, those involving discretionary judgment, deviations from established rules, or the interpretation of emotional cues, are often seen as requiring human involvement to a greater extent than standardized routine tasks (Bullock, 2019; Young et al., 2019). At the same time, experimental evidence suggests that although AI is generally met with skepticism, it is not necessarily more strongly rejected in complex tasks than in simpler ones (Ingrams et al., 2021). Importantly, this research also indicates that even the use of AI in routine tasks is not automatically welcomed. Taken together, these findings imply that individuals may not finely calibrate their trust according to the specific function AI performs; rather, broader predispositions toward AI shape their acceptance of its concrete applications. If this interpretation holds, it becomes essential to identify which individuals are willing to accept AI in complex administrative tasks before extending the analysis to its use in explicitly political contexts, as discussed by König (2023).

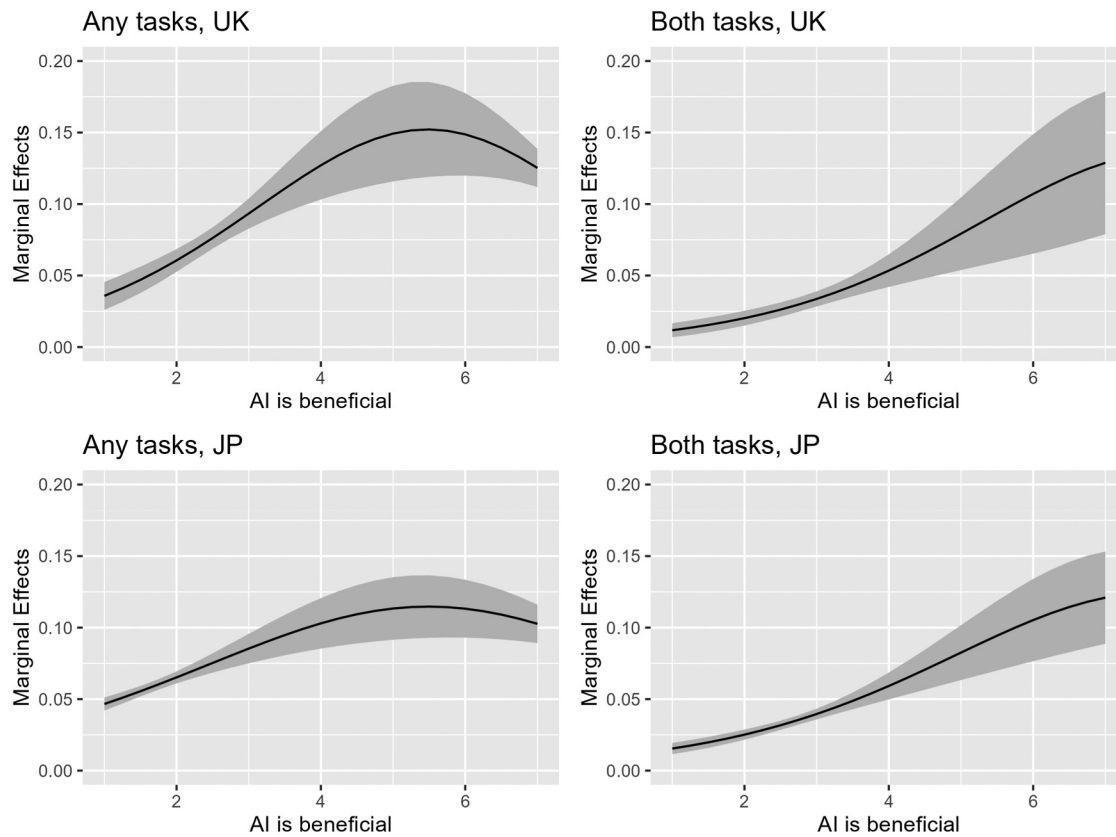


Figure 1. Marginal effects of AI benefit on dependent variables.

Table 1. Descriptive statistics.

| Variables | UK | Japan |
|---|-------------|-------------|
| N | 987 | 2,157 |
| Support AI performing simple PA routines (1–5, mean, SD) | 2.72 (1.37) | 3.08 (1.17) |
| Support AI performing complex PA routines (1–5, mean, SD) | 2.23 (1.27) | 2.75 (1.13) |
| Age (mean, SD) | 49.7 (16.7) | 49.7 (16.3) |
| Age (min, max) | 18 – 90 | 18 – 79 |
| Women (%) | 51.7% | 47.0% |
| Men (%) | 48.3% | 53.0% |
| University degree (%) | 41.0% | 53.0% |
| Left–Right ideology (0–10, mean, SD) | 4.86 (2.16) | 5.08 (1.59) |
| Trust government (1–7, mean, SD) | 2.84 (1.57) | 3.35 (1.41) |
| General social trust (1–7, mean, SD) | 3.52 (1.57) | 3.13 (1.53) |
| Risk-taking tendency (0–10, mean, SD) | 4.70 (2.15) | 4.58 (1.99) |
| AI scares me (1–7, mean, SD) | 4.88 (1.59) | 4.42 (1.42) |
| AI is beneficial (1–7, mean, SD) | 4.29 (1.62) | 4.60 (1.23) |
| AI self-efficacy (1–7, mean, SD) | 3.54 (1.75) | 3.82 (1.34) |

Unlike König (2023), we begin by examining the two outcome variables related to AI use in administrative tasks separately. We then construct an additional set of binary indicators: one coded as 1 if a respondent selects 4 or 5 on at least one item (indicating support for at least one application), and another coded as 1 if a respondent selects 4 or 5 on all items (indicating consistent support across applications). By examining the explanatory factors associated with more broadly acceptable AI use (i.e., support for at least one application) and with more demanding, consistently supported AI use (i.e., support

across all applications), we further assess the robustness of our findings.

In our analysis, we include a number of independent variables. For socio-demographic variables, we include age measured in years, and sex which takes the value 1 if the respondent is a woman and 0 if it is a man. Additionally, we include a binary variable measuring whether the respondent has completed university education or not. We also include two trust measures: one for trust in government, and one for general social trust, both measured on

a seven-point scale. We include measures for risk willingness self-placement on a left–right ideological scale, both measured from 0 to 10. To measure respondents’ views toward AI in general, we include measures for whether the respondent agrees or not with the statements “AI scares me,” “There are many beneficial application of AI” and “I know how AI technology can help me”; all three were measured on a seven-point scale with seven being the most supportive of the particular statement. As noted above, attitudes toward AI are not necessarily one-dimensional. In addition to the possibility of algorithm aversion which may dampen support for AI use, individuals may also hold distinct perceptions of its benefits or of their ability to understand and manage it. These dimensions are analytically separable and may independently shape support for AI adoption (Dietvorst et al., 2015; Kennedy et al., 2022; König et al., 2022).

Before turning to the regression analysis, we present descriptive statistics for our key variables in Table 1. These include the two main outcome variables (support for AI performing simple and complex tasks in public administration) as well as the demographic, attitudinal, and psychological predictors used in the models. The table also highlights notable cross-national differences, with Japanese respondents generally expressing higher average

support for AI than their UK counterparts, particularly for simple administrative tasks.

Analysis

We begin the analysis by comparing public support for AI in public administration across the UK and Japan. As Table 1 shows, support for AI is consistently higher in Japan than in the UK (simple, $t = 7.2$; complex, $t = 10.9$), and respondents in both countries are more comfortable with AI handling simple administrative tasks than complex decision-making (UK, $t = 8.1$; JP, $t = 9.4$). In the UK, the mean level of support for simple tasks is 2.72 on a 5-point scale, compared to 2.23 for complex tasks. In Japan, support is higher overall, with a mean of 3.08 for simple tasks and 2.75 for complex ones. These differences suggest that while citizens in both contexts are open to automation in low-stakes, routine government functions (such as data entry or automated scheduling) they are far more cautious about the delegation of more complex administrative responsibilities to AI systems. This pattern provides an important backdrop for understanding the regression results presented in the following tables.

To examine the drivers of support for AI in public administration, we estimate a series of OLS regression models, presented in Table 2. Models 1–4 refer to the UK sample, while Models 5–8 cover Japan. For each

Table 2. Regression results for support of AI in public administration tasks (UK and Japan, simple and complex tasks).

| | Dependent variables: | | | | | | | |
|------------------|----------------------|----------------------|----------------------|----------------------|-----------------------|----------------------|------------------------|----------------------|
| | Simple PA tasks UK | | Complex PA tasks UK | | Simple PA tasks Japan | | Complex PA tasks Japan | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Age | −0.008** (0.003) | −0.001 (0.002) | −0.006* (0.002) | −0.000 (0.002) | −0.005** (0.002) | −0.002 (0.001) | −0.008*** (0.001) | −0.004** (0.001) |
| University | 0.453*** (0.089) | 0.213** (0.076) | 0.301*** (0.084) | 0.123 (0.077) | 0.313*** (0.050) | 0.239*** (0.046) | 0.190*** (0.049) | 0.137** (0.046) |
| Women | −0.432*** (0.083) | −0.176* (0.072) | −0.412*** (0.079) | −0.197** (0.073) | −0.211*** (0.051) | −0.195*** (0.047) | −0.172*** (0.049) | −0.132** (0.046) |
| Trust government | 0.134*** (0.029) | 0.063* (0.025) | 0.096*** (0.027) | 0.040 (0.025) | 0.076*** (0.018) | 0.047** (0.017) | 0.086*** (0.018) | 0.061*** (0.017) |
| Trust people | 0.060* (0.028) | 0.033 (0.024) | 0.050+ (0.027) | 0.032 (0.024) | 0.035* (0.017) | 0.031* (0.015) | 0.025 (0.016) | 0.018 (0.015) |
| Take risks | 0.024 (0.020) | −0.004 (0.017) | 0.030 (0.019) | 0.005 (0.017) | 0.070*** (0.013) | 0.024* (0.012) | 0.072*** (0.012) | 0.030** (0.012) |
| Left-right | 0.042* (0.021) | 0.027 (0.017) | 0.050* (0.020) | 0.038* (0.018) | 0.031* (0.016) | 0.012 (0.014) | 0.018 (0.015) | 0.004 (0.014) |
| AI scares me | | −0.162*** (0.025) | | −0.160*** (0.025) | | −0.038* (0.016) | | −0.072*** (0.016) |
| AI is beneficial | | 0.355*** (0.025) | | 0.230*** (0.025) | | 0.328*** (0.020) | | 0.225*** (0.019) |
| AI self efficacy | | 0.056* (0.025) | | 0.063* (0.025) | | 0.102*** (0.018) | | 0.154*** (0.018) |
| Constant | 2.212*** (0.224) | 1.419*** (0.268) | 1.804*** (0.211) | 1.432*** (0.272) | 2.392*** (0.131) | 0.984*** (0.154) | 2.314*** (0.127) | 1.207*** (0.152) |
| Observations | 987 | 987 | 987 | 987 | 2157 | 2157 | 2157 | 2157 |
| R2 | 0.122 | 0.388 | 0.091 | 0.271 | 0.078 | 0.228 | 0.067 | 0.189 |
| R2 Adj. | 0.115 | 0.382 | 0.084 | 0.264 | 0.075 | 0.225 | 0.064 | 0.185 |

Note: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

country, Models 1 and 2 (UK) and 5 and 6 (Japan) predict support for AI performing simple administrative tasks, while Models 3 and 4 (UK) and 7 and 8 (Japan) focus on complex tasks. The odd-numbered models include a baseline set of demographic, ideological, and trust-related variables. The even-numbered models extend these by adding psychological factors, including respondents' attitudes toward AI's benefits, perceived risks, and self-efficacy.

Table 3 reports the results of binomial logistic regression models using a binary outcome variable that captures general support for AI in public administration. Respondents are coded as 1 if they supported AI in at least one of the two task domains (simple or complex) and 0 otherwise. The models include the same set of explanatory variables as in Table 2 and provide a complementary test of broader receptiveness to AI-based innovation in public sector settings.

As shown in Table 1, citizens in both the UK and Japan express greater support for AI performing simple public administration tasks than for complex ones. The regression results in Table 2 reinforce this pattern. While the determinants of support are broadly similar across task types and contexts, the magnitude and consistency of effects tend to be stronger for simple tasks, particularly in the UK.

Several individual-level characteristics are associated with support for AI in public administration. Across nearly all models, holding a university degree is

positively and significantly related to AI support, while being older or female predicts lower support. These effects are consistent across both countries and both task domains. Political orientation also plays a role, with more right-leaning respondents in the UK expressing higher support for AI use. This ideological gradient is weaker in Japan, where support is less clearly structured by left–right position.

Institutional trust shows a more nuanced pattern. Trust in government emerges as a robust and consistent predictor of AI support across countries and models. By contrast, generalized social trust (trust in other people) has a weaker and more variable effect. In the UK, trust in government is significant in both simple and complex task models, whereas trust in people is only marginally significant or non-significant. In Japan, both trust variables reach significance, but the coefficients for trust in government are slightly larger, suggesting that confidence in public institutions plays a more central role than interpersonal trust in shaping citizens' receptiveness to administrative automation.

Finally, the extended models (Models 2, 4, 6, and 8) highlight the importance of psychological orientations toward AI. Respondents who believe AI is beneficial and who report higher AI self-efficacy are significantly more likely to support its use, while those who say AI scares them are markedly less supportive. These variables contribute substantially to model performance, and their effects are comparable in strength to those of

Table 3. Logistic regression results for general and consistent support for AI in public administration (UK and Japan).

| | Dependent variables | | | | | | | |
|------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| | Any tasks, UK | | Both tasks, UK | | Any tasks, JP | | Both tasks, JP | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Age | −0.015*** (0.004) | −0.008 (0.005) | −0.005 (0.006) | 0.006 (0.006) | −0.014*** (0.003) | −0.011*** (0.003) | −0.007* (0.003) | −0.002 (0.004) |
| University | 0.646*** (0.148) | 0.397* (0.166) | 0.347+ (0.189) | 0.041 (0.204) | 0.571*** (0.094) | 0.518*** (0.098) | 0.444*** (0.118) | 0.363** (0.123) |
| Women | −0.653*** (0.141) | −0.364* (0.161) | −0.789*** (0.184) | −0.475* (0.199) | −0.432*** (0.094) | −0.446*** (0.099) | −0.517*** (0.119) | −0.513*** (0.125) |
| Trust government | 0.145** (0.049) | 0.064 (0.056) | 0.089 (0.062) | 0.016 (0.065) | 0.077* (0.034) | 0.051 (0.036) | 0.057 (0.042) | 0.037 (0.044) |
| Trust people | 0.113* (0.049) | 0.099+ (0.056) | 0.005 (0.062) | −0.016 (0.066) | 0.056+ (0.032) | 0.058+ (0.033) | −0.034 (0.039) | −0.040 (0.040) |
| Take risks | 0.037 (0.034) | 0.001 (0.039) | 0.058 (0.043) | 0.019 (0.046) | 0.103*** (0.024) | 0.050* (0.025) | 0.134*** (0.030) | 0.069* (0.031) |
| Left-right | 0.078* (0.035) | 0.080* (0.040) | 0.070 (0.044) | 0.072 (0.046) | 0.001 (0.029) | −0.029 (0.031) | 0.052 (0.035) | 0.027 (0.037) |
| AI scares me | | −0.280*** (0.058) | | −0.185** (0.066) | | −0.072* (0.036) | | −0.087* (0.042) |
| AI is beneficial | | 0.679*** (0.071) | | 0.585*** (0.088) | | 0.495*** (0.047) | | 0.545*** (0.062) |
| AI self-efficacy | | 0.033 (0.056) | | 0.120+ (0.069) | | 0.159*** (0.040) | | 0.278*** (0.050) |
| Constant | −1.142** (0.379) | −2.966*** (0.640) | −2.097*** (0.487) | −4.596*** (0.818) | −0.717** (0.248) | −2.964*** (0.367) | −2.104*** (0.311) | −5.207*** (0.493) |
| Num.Obs. | 987 | 987 | 987 | 987 | 2157 | 2157 | 2157 | 2157 |
| AIC | 1220.7 | 1017.1 | 857.1 | 754.1 | 2789.3 | 2612.3 | 2045.8 | 1882.4 |
| Log.Lik. | −602.331 | −497.543 | −420.559 | −366.038 | −1386.647 | −1295.172 | −1014.922 | −930.216 |

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

institutional trust or education. Taken together, the findings suggest that public support for AI in public administration is shaped by both longstanding civic attitudes and newer, technology-specific beliefs. The explanatory power of the AI attitude variables points to the importance of public engagement and education in shaping future adoption.

Table 3 shifts focus from task-specific attitudes to a broader indicator: whether respondents express support for AI in public administration in any context. Using logistic regression, we estimate eight models (four for the UK and four for Japan) with the same covariates as Table 2. The “Any tasks” variable is coded as 1 if respondents express support for AI use in either simple or complex tasks, and 0 otherwise. By contrast, the “Both tasks” variable is coded as 1 only when respondents support AI use in both simple and complex tasks. As in the previous analysis, the odd-numbered models include demographic, ideological, and trust variables, while the even-numbered models incorporate additional predictors capturing perceptions of and emotions about AI.

The results in Table 3 are broadly consistent with those observed in Table 2, underscoring the key determinants of AI support across contexts. In both the UK and Japan, being male, younger, and having a university degree remain strong and statistically significant predictors of a general tendency to support AI use. However, the effects of age and university education are somewhat weaker in the UK than in Japan. The broader cross-national pattern also persists: ideological orientation continues to be a significant predictor in the UK, whereas risk tolerance remains more salient in Japan. In addition, higher levels of trust in government and interpersonal trust are associated with more permissive attitudes toward AI use. By contrast, demographic characteristics are less predictive when the outcome is defined as consistent support for AI use in both simple and complex tasks. Most notably, the extended models show that technology-specific attitudes are highly influential with respect to attitudes toward AI adoption. This pattern is especially pronounced in consistent support for AI use in government, whether for simple or complex tasks. Positive views of AI and higher self-efficacy are associated with increased support, while fear or anxiety about AI is negatively related to it. The size and consistency of these coefficients suggest that these beliefs operate as important psychological gateways to public approval.

We further estimated average marginal effects from the logistic regression models to assess the substantive impact of the independent variables on attitudes toward AI use. For most explanatory variables, marginal effects were relatively modest and stable. A notable exception,

however, concerns perceptions of AI’s benefits. As illustrated in Figure 1, respondents in both countries who perceive AI as highly beneficial are substantially more likely to support its use in government. This association is particularly pronounced when support is defined as endorsement of AI use across both simple and complex tasks. Consistent with previous works, these findings suggest that perceived benefits may offset, or even outweigh, tendencies toward algorithm aversion (Kennedy et al., 2022; König et al., 2022).

Taken together, the results from Tables 2 and 3 offer a coherent picture of the factors shaping public support for AI in public administration. While overall support levels differ between the UK and Japan, with Japanese respondents expressing greater openness, both countries exhibit a clear preference for delegating simple administrative tasks to AI rather than complex ones. Across both contexts, demographic characteristics such as education, age and gender play consistent roles, with university graduates more supportive and older or female respondents more hesitant. Institutional trust, especially trust in government, emerges as a reliable predictor of support, though its effects are more pronounced in the UK.

Notably, the introduction of AI-specific attitudes into the models significantly improves explanatory power. Beliefs about the benefits of AI, confidence in one’s ability to understand it, and emotional responses such as fear or anxiety all show strong and consistent associations with support. In particular, beliefs about the benefits of AI emerge as especially influential predictors. These findings suggest that public receptivity to AI in the public sector is not purely a function of political or social background, but also hinges on how people perceive and emotionally relate to the technology itself. In short, acceptance of government AI initiatives is shaped by a blend of civic predispositions and tech-specific beliefs: an insight with clear implications for policymakers navigating the rollout of AI systems in public life.

Discussion and implications for public administration

The empirical results offer several insights for public administration practice in both the UK and Japan. They highlight not only the attitudinal drivers of support for AI but also the kinds of strategies that might improve public acceptance of these technologies in government. In this section, we explore the implications of our findings for digital governance and public sector management, with a particular focus on how bureaucracies can respond to concerns around AI by addressing the variables that most strongly influence support.

These include public trust in government, personal attitudes toward AI, and concerns about fairness and transparency. We also reflect on the importance of cross-national comparison. While institutional cultures in the UK and Japan differ, the challenges of implementing AI in a legitimate, publicly accepted manner are shared.

One clear implication is that government agencies in both countries must balance the efficiency benefits of AI with public expectations for accountability and meaningful human involvement. As our results and prior research show, highly personalized and complex services, especially those requiring discretion or contextual judgment, are more likely to be perceived as necessitating human oversight than simple routine tasks (Bullock, 2019; Young et al., 2019). Concerns about granting AI substantive decision-making authority are argued (König et al., 2022), and our findings indicate that reservations persist regarding the use of AI for complex administrative functions. At the same time, however, AI adoption is not met with uniform resistance. Support is more prevalent among university graduates, younger individuals, men, and those who exhibit higher levels of trust in government. Policymakers may consider a gradual implementation strategy, beginning with less controversial, routine applications that command broader acceptance.

A gradual, step-by-step approach to expanding AI adoption is desirable, as it enables governments to communicate the tangible benefits of the technology more effectively. Governments can influence these perceptions by showcasing small but meaningful success stories, such as time savings or service improvements. Successful implementation in routine tasks may help citizens recognize its practical value and convenience, thereby fostering greater openness to more advanced applications. Indeed, our analysis suggests that perceived benefits are closely linked to increased tolerance for broader AI use. At the same time, policymakers must remain attentive to the persistent and often powerful fears associated with AI deployment. Addressing these concerns requires a multifaceted strategy grounded in transparency and public engagement. Government agencies should clearly explain, in accessible language, how AI systems are designed and used. Moreover, human oversight should be actively leveraged to compensate for the limitations of algorithmic transparency and explainability that citizens reasonably expect from public institutions but that are often lacking in AI-driven decision-making processes (Haesevoets et al., 2024; Lee, 2018; Starke & Lünich, 2020).

While AI-specific attitudes are strong predictors of support, broader civic trust matters too. This suggests that maintaining institutional trustworthiness, through accountability, ethics training and independent evaluation, will indirectly support AI adoption. Oversight

bodies in both countries, such as the Information Commissioner's Office in the UK or the administrative evaluation mechanisms in Japan, should be empowered to monitor and audit AI systems for fairness, privacy, and effectiveness. Equally important are mechanisms for appeal: if a citizen believes a decision was unfairly made by an AI-assisted process, they should be able to request human review. In both Japan and the United Kingdom, prior research indicates public support for a "human-in-the-loop" model of AI governance (Aoki, 2021; Haesevoets et al., 2024). This reinforces the message that AI operates within, rather than above, the boundaries of democratic governance.

Although our findings show many similarities across the two countries, national context still matters (Wenzelburger et al., 2024). In Japan, by contrast, where individual risk tolerance appears to shape support for AI adoption more strongly, a governance approach that brings together experts, practitioners, and citizens to mitigate perceived risks may be particularly effective in addressing skepticism and signaling institutional caution. Even when AI use in administration is widely regarded as beneficial, the introduction of more ambitious or experimental technologies may trigger public backlash, making careful management of uncertainty essential. At the same time, ideological dynamics may shape support for AI adoption in the UK, where media and civil society are more openly critical of government tech, public managers should prioritize proactive transparency and anticipate political sensitivities. If political debates become polarized, for example, with left-leaning actors emphasizing concerns about digital inequality and right-leaning actors highlighting efficiency and innovation, such divisions could impede the broader expansion of AI use. Future AI governance will likely depend on carefully balancing the promotion of convenience and performance gains with sensitivity to emerging political and social cleavages.

Improving public support for AI in government will require action on several fronts: deploying systems transparently, engaging the public in design and evaluation, ensuring accountability, and focusing on real-world benefits. Our findings suggest that citizens in both countries are open to these technologies, but only if their concerns are taken seriously. Legitimacy, not just efficiency, must remain the guiding principle for public sector AI.

Conclusion

This study set out to examine public attitudes toward the use of artificial intelligence in public administration in the United Kingdom and Japan. Drawing on original

survey evidence, we explored how citizens in these two advanced democracies respond to different types of AI applications in government. Our findings suggest that while public support exists, it is conditional and context-dependent. Across both countries, respondents are more receptive to AI being used for simple, routine administrative tasks than for complex or discretionary decisions. This reflects a broader desire for human oversight and accountability in government operations, even as interest in technological innovation grows.

We identified several key drivers of support for AI in public administration. Younger respondents and those with higher levels of education were more likely to support government use of AI, as were individuals who expressed trust in government, held positive views about AI's benefits, and felt confident using digital tools. In particular, respondents who strongly emphasize the benefits of AI tend to support the introduction of more advanced applications. Conversely, fear of AI emerged as a consistent barrier to support. These patterns were remarkably similar in both the UK and Japan, indicating a shared attitudinal structure despite cultural and institutional differences.

Nonetheless, the degree of support and the salience of certain factors varied across countries. Japanese respondents expressed higher average support for AI in both simple and complex tasks but also reported greater caution, particularly regarding fairness and data privacy. This tension reflects Japan's dual reputation as a technological innovator and a society attuned to social risks. In the UK, public opinion appeared somewhat more polarized, with support clustered among those who perceive clear service improvements and safeguards for human control. Both countries therefore face the challenge of balancing efficiency and innovation with accountability and transparency.

Our analysis yields robust findings that underscore the importance of perceived benefits in shaping support for AI, while remaining broadly consistent with prior research. Nevertheless, several limitations should be acknowledged. First, the survey was conducted online, which may have attracted respondents who are more technologically engaged and thus potentially more receptive to AI than the general population. In particular, the Japan sample includes fewer respondents at the oldest ages, raising concerns about underrepresentation of older cohorts. Moreover, attitudes toward AI use may reflect heterogeneous interpretations shaped by respondents' individual experiences and exposure to technology. Because the survey relies partly on abstract formulations of AI use, respondents may have evaluated the questions based on differing

assumptions. Future research would benefit from employing more specific and contextually grounded question designs to reduce interpretive variation and allow for more precise assessment of public attitudes.

Despite these limitations, our findings carry important implications for public administrators and policy-makers. Support for AI in government cannot be taken for granted. It must be earned through trust-building measures: ensuring clear human oversight, being transparent about how AI is deployed, engaging the public meaningfully in the process, and demonstrating tangible service improvements. Institutional trust and perceived benefits are not just background variables; they are levers that governments can strengthen through their communication and governance strategies.

Integrating AI into public administration is not solely a technical endeavor. It is a question of legitimacy, public values, and citizen engagement. As AI technologies continue to evolve, so too will public expectations about how they should be used. Future research should continue tracking these trends and assessing the effectiveness of various government approaches to cultivating support. By placing citizens at the center of AI governance, such as by responding to people's hopes and fears, public administrations in the UK, Japan and beyond will be better positioned to realize the potential of AI while maintaining democratic accountability.

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Author contributions

CRedit: **Steven David Pickering:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Validation, Writing – original draft, Writing – review & editing; **Martin Ejnar Hansen:** Conceptualization, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing; **Yosuke Sunahara:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Project administration, Writing – original draft, Writing – review & editing.

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Ethics approval statement

The Ethical Review Committee of Brunel University London approved this research, reference number 35,290-LR-Jan/-2022-37313-1.

Replication data

Full anonymized replication data and code are available from the Harvard Dataverse, at: <https://doi.org/10.7910/DVN/AWHYKA>.

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