Discover Artificial Intelligence

Brief Report

Adoption of artificial intelligence in the judiciary: a comparison of 28 advanced democracies

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Abstract
Artificial Intelligence (AI) is increasingly used worldwide to make decisions, be it by public administrations, industry, banks, or insurers. One area with a particularly high impact on citizens is its use in judiciary processes. To this day, there has been little investigation into why countries decide to adopt AI in this area. In this article, we show that the mere promise of efficiency gains is not enough of an explanation for why countries adopt AI within judiciary processes. Instead, we show that the administrative burden (as measured by the number of days to trial), a government's leaning within the political spectrum (namely towards the left), and the level of adoption of technology by governments in neighboring countries predict countries' announcement to adopt AI in their judiciary. Taken together, our findings derived from a data analysis of 28 advanced democracies constitute an important step towards a better understanding of the factors shaping AI's integration into judiciary processes.

1 Introduction

Automation within public administration has gained global momentum [1], with artificial intelligence (AI) technologies being increasingly implemented to streamline government processes that directly impact citizens [2, 3], and with keen interest from legislators on the topic [4]. One area drawing significant attention is the judiciary, where AI is beginning to support various stages of legal proceedings [5]. As the judiciary plays an important role in deciding citizen disputes and thereby significantly interferes in social relations, it is a particularly interesting use case to study the motivations behind AI adoption [6].

The integration of AI technologies into legal proceedings constitutes a far-reaching regulatory reform that may fundamentally alter traditional judicial practices, changing the ways policies are made and decisions are taken in a political system. Such reforms generally do not come lightly and are believed to be not only driven by utility considerations but by a broader range of political, functional, and/or ideational motivations [7]. While the promise of efficiency gains and, thereby, a reduction of current backlogs in courts has driven much of the initial interest, this premise alone is unlikely to account for the complexities surrounding the integration of AI in judicial systems [8].

This article is organised into four key sections. Section 2 outlines the theoretical framework, positioning AI adoption in the judiciary as a form of regulatory reform whose adoption can be explained by looking at political, functional, and ideational factors. Section 3 describes the methodology employed. Section 4 presents the findings, showing that all three factors are statistically significant in influencing AI adoption in judicial systems. Section 5 provides a broader interpretation of these results, situating them within the context of judicial reform while also addressing the study's limitations

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and avenues for future research. Together, these sections build an exploratory understanding of the factors shaping AI's integration into judiciary processes.

2 Theorising adoption

There are various frameworks that aim to explain technology adoption, with the most cited ones the Technology Acceptance Model (TAM; [9]), the Unified Theory of Acceptance and Use of Technology (UTAUT [10]), and respective iterations on them [11]. Recent years have witnessed a proliferation of analyses of these frameworks across many domains, most of them focusing on adoption of *users* and by the *private sector* [12]. Additionally, with the emergence of more advanced technology, more studies have emerged specifically focusing on AI adoption but have, once more, largely focused on *user* adoptions in the private sector [13]. The findings of a review of 60 studies indicate that the most influential factors in AI adoption are perceived usefulness, performance expectancy, attitudes, trust, and effort expectancy, mirroring that the most used and cited theory for *user* acceptance was the extended Technology Acceptance Model (TAM) [13].

Some of these frameworks have also been applied to explore technology adoption in the public sector, uncovering several factors influencing adoption. With regard to the judiciary, notably, studies have highlighted that technology acceptance is primarily linked to perceptions of usefulness [14, 15], utility of technology [16] and perception of trust [17]. The utility factor in technology adoption is further supported by numerous studies in the context of the COVID-19 pandemic, with one study highlighting that the legal profession has embraced technology as an important tool for enhancing access to justice [18]. Once again, a host of studies has looked at drivers behind *user* adoption of e-government services [19, 20]—a question which is beyond the scope of this research. A few others have focused on the factors that shape the transition of public services to the digital realm, highlighting the role of: the need to streamline administrative tasks and enhance accessibility for users [21], the level of democracy and regional competition [22, 23], perceived organisational benefits, in-house capacities and clear strategies [2].

At a very basic level, it is important to note that the capacity to pursue digital transformation in the public sector—particularly in sensitive domains such as the judiciary—is shaped by broader institutional conditions. In particular, high levels of institutional quality, such as those discussed in the literature on the "quality of government" [24], appear to be a necessary precondition for governments to undertake and implement far-reaching reforms involving AI. This literature underscores the importance of effective, impartial, and corruption-free institutions in enabling states to carry out complex regulatory changes—conditions that are typically met in advanced democracies and that set the stage for the adoption of AI in judicial systems.

At the same time, it is important to emphasise that the adoption of e-government services, in particular those involving AI components, constitute far-reaching regulatory reforms that face significant political, ideational, and functional hurdles before their adoption [25]. The reason is that such reforms are likely to alter decision-making processes within government and that those involved in these processes may fear to lose out from the reforms. Especially in advanced democracies, which are very path-dependent [8] due to the presence of multiple veto points that can block substantial change [26], institutional reforms are unlikely to be the result of utility considerations alone. Even governments intent on doing the "right" thing often fail to do so because of structural or political constraints or because they are simply unaware of how to match problems to potential solutions. For example, when examining legal technology in contemporary USA and China, Wang [27] highlights that the characteristics of legal tech are closely tied to each country's political landscape (centralized versus decentralized governance), legal system objectives (whether aimed at increasing efficiency or enhancing justice), and judicial structure. Another study on e-justice in Switzerland and Brazil emphasises the interplay of innovation features (e.g., usability), organisational aspects (team dynamics), and environmental influences (e.g., centralisation, federalism, and legislation) [7]. Additionally, a study on implementing technology in the Canadian justice sector highlights that learning from the mistakes and successes of others plays an important role in fostering adoption [28].

With these insights in mind, we develop a theoretical framework for explaining AI adoption in the judiciary that accounts for functional, political, and ideational factors. These factors have been shown to drive the adoption of other regulatory reforms in advanced democracies [25, 29] and are hence well suited for an exploratory analysis in our area of interest. Moreover, our framework is based on the well-established insight that governments may embark on regulatory reforms for both substantive reason (i.e., they want a reform to address a particular problem) and for more symbolic reasons (i.e., they are less interested in the reform's actual effects and more in the political message it sends, see e.g. [30, 31]). To encapsulate these ideas in a theoretically parsimonious way, we focus on three concrete factors: (i) the degree

of overburdening of the judiciary, (ii) the political position of the government, and (iii) diffusion effects. In the following, we discuss these factors in detail and formulate expectations on how they should influence AI adoption in the judiciary.

2.1 Functional pressures: overburdening of the judiciary

The proliferation of rules and regulations has been identified as a ubiquitous feature of modern democracies [32]. As the administrative capacities necessary to implement ever more rules and regulations have not grown to the same extent, administrative overburdening has become a widespread phenomenon in advanced democracies [33]. While this finding applies to public administrations in general, it has also been observed in the judiciary. Many judiciaries [34] currently work at or beyond their capacity limit and struggle with ever-growing case backlogs and longer durations to trial. Administrative overburdening creates pressure for governments to look for ways to slow down workload growth and allow administrations to shoulder greater workloads by streamlining and automating procedures. One example are regulatory offsetting schemes that seek to compel governments to compensate for the production of additional rules by simultaneously abolishing existing provisions and associated burdens [29]. We thus expect that countries with overburdened judiciaries are more likely to adopt an AI project than countries whose judiciary faces no such problem.

H1: The average duration of a case to trial has a positive effect on the decision to adopt AI in the judiciary.

2.2 Political factors: the position of the government

Political parties are known to be both vote and policy seekers [31]. They compete for office by championing issues that their supporters care about, and, once in government, they seek to adopt policies that benefit their supporters and align with their own ideological orientations. Left-leaning parties are generally known to advocate for an expansive and influential government and broad-based access to public services. Left-leaning parties have historically championed a comprehensive welfare state, supported government oversight of markets [35], and focused on social protection and human capital creation [36, 37]. Right-leaning parties, on the contrary, have been shown to champion a smaller state that restricts access to social services, contingent on specific criteria. In the US, for example, Republican governments, which traditionally oppose generous welfare programs, have repeatedly managed to put a high administrative burden on welfare recipients so as to make it harder for them to claim the benefits they are entitled to [38]. We thus expect that left-leaning parties are generally more likely to adopt regulatory reforms that promise to make the state more responsive to its citizens. Since many AI projects in the judiciary seek to increase access to judicial services that citizens are entitled to (e.g., by making the law more transparent through anonymized case publications, by making the law more understandable to laypeople by adapting the language to the vernacular, see for more examples [3, 5]), we expect left-leaning parties to be positively associated with AI adoption while this should not be the case for right-leaning parties.[1]

H2: Left-leaning governments are more likely to decide to adopt AI in the judiciary than right-leaning governments.

2.3 Matching solutions to problems: the role of diffusion effects

Governments rarely act entirely independently when attempting to tackle specific political challenges. Instead, they often draw inspiration from the experiences and policy solutions of other governments [41, 42]. This tendency is even more pronounced when there are multiple regulatory options available, allowing governments to choose among several potential solutions rather than being limited to a single approach. Policy diffusion is especially likely between neighboring countries that are closely interlinked through trade relationships and political alliances, as these connections facilitate the sharing and adaptation of ideas and policies [43]. Neighboring countries are especially prone to drawing insights from one another's experiences with various policies and to adopting each other's attempts at problem-solving [44, 45]. Based on these insights, we expect that the level of adoption of technology in neighboring countries positively impacts a government's decision to adopt AI in the judiciary.

H3: The level of adoption of e-government in neighboring countries has a positive effect on a government's decision to adopt AI in the judiciary.

[1] We note that right-wing parties are generally pro law and order [39, 40]. However, as described below in the section Methodology, the projects captured do not solely focus on seeking to enhance law and order, and in fact, very few even focus on criminal matters at all (see the Sect. 5 for this).

3 Methodology

3.1 Dependent variable

We are interested in capturing data on the *first AI project implemented by a country in the judiciary* to assess the hypotheses; this corresponds to data for years 1997–2024 (1997 being the earliest year for which we found a project for the countries under study, and 2024 corresponding to when we conducted the research). From this, one component to capture is already evident: the projects are in different stages (we categorised them between not started, pilot/ongoing, and implemented). Furthermore, in order to analyse H2, it is important to capture when the project was initiated. We also applied the typology from Guitton et al. [46] to capture whether a project is primarily geared towards increasing accessibility to the law or towards improving its efficiency, as well as the *area of implementation* (courts, prosecutors, notaries) and what purpose exactly the project seeks to achieve (anonymisation, transcription, information extraction, etc.). We therefore captured 5 variables: year, stage, aim, area, and purpose.

The sources for the data were twofold. First, we manually looked for information for each country for which sources for the independent variables existed (see below). Second, we cross-checked and complemented this information with data from the Council of Europe's resource on "cyberjustice and artificial intelligence" [47]. It is also noteworthy that we only relied on secondary sources about the existence and data of each programme. In order to minimise errors, two of the authors independently went through the data collection.

The list of 28 countries was primarily derived from the intersection of countries for which we could find information for the different independent variables. We sought to maximise this dataset and, in a second step, eliminated countries whose socio-political structures were judged to be too different from the rest of the dataset, particularly in terms of democratic institutions (e.g. Azerbaijan, Morocco), since our theory is specifically concerned with advanced democracies.

The criterion for inclusion was for a country itself to label the technology that they were using as "AI". Regarding the lack of accepted consensus around a definition of AI,[2] this approach suited our research goal, as we are interested in *why* countries would seek to present themselves as (early) adopters of AI. Following this, two specific types of projects were excluded, as they were systematically not presented under the "AI" label: projects related to risk-assessment-instruments, and those related to the automatic assignment of cases.

The result of the data collection shows a rather homogeneous dataset, with only 5 countries with no implementation at all. 86% of the projects collected were in the context of courts, 10% for adjudication, and 5% for the overall justice system (note that one project was for both court and adjudication within the administration). Furthermore, most projects focused on anonymising court records for their release to the general public; the second most frequent category of projects concerned automatic speech-to-text transcription of court hearings (see Fig. 1).

3.2 Independent variables

We used the three different metrics and sources for each hypothesis as listed in Table 1.

The dataset for H2 only included data up to 2022. As we carried out a survival analysis (see below), this was sufficient for all countries whose adoption of AI in the judiciary came before or in 2022. For 3 other countries (namely: Romania, Slovenia, Spain), we completed the dataset by adding the composition of right-wing members in the government manually following Armingeon et al. [49] for the years 2023–2024.

We took the subset of countries for which data was available for each of the three introduced operationalisations. This led to slightly different datasets for H1/H3 and H2, with 25 countries considered in H1/H3 and 28 for H2 (the complete list is provided in Appendix A).

3.3 Data analysis

For H1 and H3, we carried out separate simple linear regressions including each of the five dependent variables, as this is a standard method within policy/political science to attempt at identifying potential relations between different sets

[2] https://cacm.acm.org/opinion/between-the-booms-ai-in-winter/.

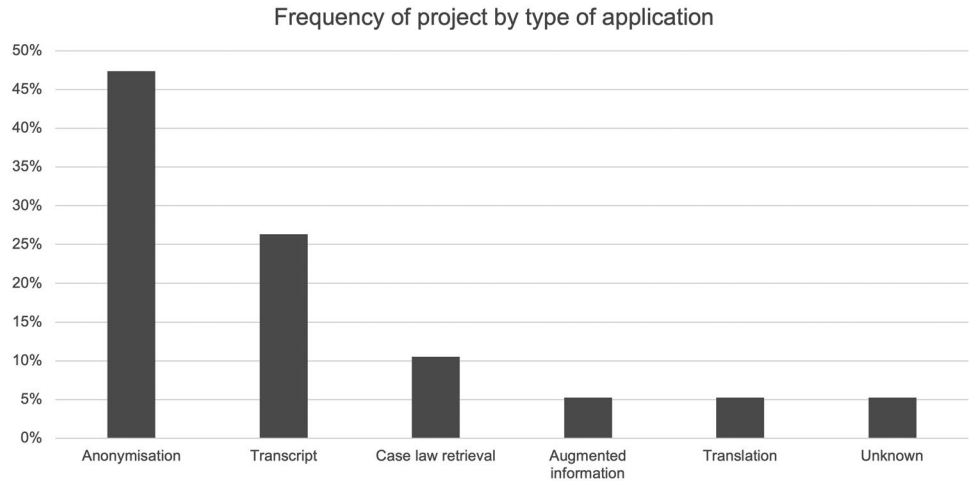


Fig. 1 Frequency of projects by types of application

of variables and is in line with how we posited the hypotheses [51]. This yielded a set of 5 linear regressions, with b_0 the intercept and $b_{i>0}$ the linear regression coefficient. In all models, we also control for the quality of government [52] and GDP per capita [53] by taking 2022 data to take into account previous evidence on the factors that may drive AI adoption in government [6, 24]:

$$Y_{year} = b_0 + b_1X_{H1} + b_2X_{H2} + b_3X_{H3} + b_{GovernmentQuality}X_{GovernmentQuality} + b_{GDPperCapita}X_{GDPperCapita}$$
$$Y_{stage} = b_0 + b_1X_{H1} + b_2X_{H2} + b_3X_{H3} + b_{GovernmentQuality}X_{GovernmentQuality} + b_{GDPperCapita}X_{GDPperCapita}$$
$$Y_{aim} = b_0 + b_1X_{H1} + b_2X_{H2} + b_3X_{H3} + b_{GovernmentQuality}X_{GovernmentQuality} + b_{GDPperCapita}X_{GDPperCapita}$$
$$Y_{area} = b_0 + b_1X_{H1} + b_2X_{H2} + b_3X_{H3} + b_{GovernmentQuality}X_{GovernmentQuality} + b_{GDPperCapita}X_{GDPperCapita}$$
$$Y_{purpose} = b_0 + b_1X_{H1} + b_2X_{H2} + b_3X_{H3} + b_{GovernmentQuality}X_{GovernmentQuality} + b_{GDPperCapita}X_{GDPperCapita}$$

Furthermore, we conducted one-way ANOVA tests on the stage of the projects to try to evidence differences between the different groups, and in a second step, we merged the stage of projects so that they could fit within two groups only: those countries with no project started vs. those with an ongoing project *or* one already implemented. This allowed us to carry out one-tail t-tests.

For H2, further in line with the hypothesis, we carried out an event history analysis, which is a well-suited form of analysis when the phenomenon under a study has a duration with an occurrence at a discrete point in time (so called "time-to-event data"), and which allows us to identify a likelihood of a variable to trigger an "event" (see for a similar data analysis method [29]. In our case, every country is "at risk" of starting an AI project in its judiciary and this represents therefore the event under consideration; once this has occurred, the country is then "censored" (removed) from the dataset for the subsequent years. The unit of analysis is therefore the country level, time periods are years, and all data are continuous as explained in the section above. We take as a starting year 1995, slightly before the year of the first project on the compiled list (1997 in Austria). This allows us to compute the probability of *survival* to the time t $Pr(T_i \geq t)$, with the following model description:

$y_{t,c}$: binary component that captures whether a country has started an AI project in the judiciary
t: time expressed in year
c: country

We then compute a univariate Cox's regression on the survival function for its statistical significance. In a second step, we repeated the event history analysis by adding as a treatment the aim followed behind kickstarting a project (whether for efficiency gain or to promote accessibility to the law).

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Table 1 Sources and metrics for hypotheses

H#	Years	Metric	Source
H1	2022	Disposition time: average duration to trial (in days) for criminal, civil, and administrative trials	European Commission for the Efficiency of Justice [58]
H2	1997[a]–2024	Political position of a government, measured as "the proportion of cabinet posts of right-wing parties in relation to total cabinet posts, weighted by the number of days in office in a given year" [2]	Comparative Political Data Set [2]
H3	2022	E-government development index: Difference between a country's index and the average across its neighbouring countries	United Nations [59]

[a]1997 corresponds to the first year that an AI project surfaces in the subset of the 28 selected countries

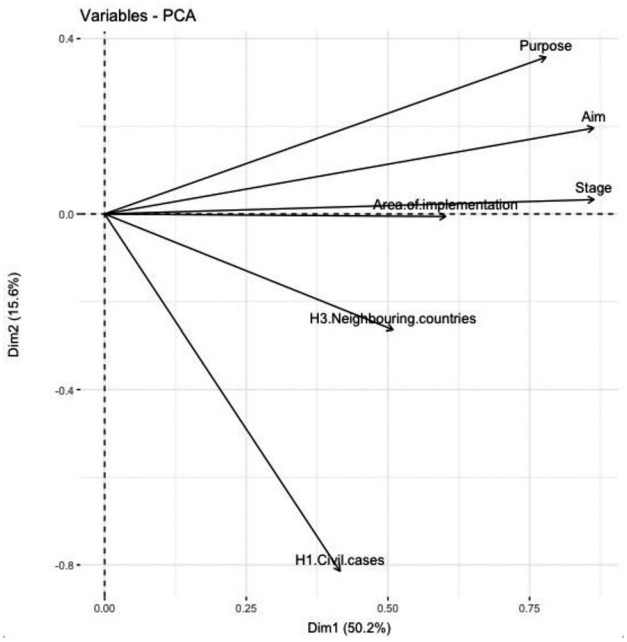


Fig. 2 Principal component analysis for the dependent variables and H1/H3. As the vectors are not orthogonal, this can be taken as an indication of possible statistical relation between them

Table 2 Results are statistically significant for H1 and H3 when tested against the dependent variable "stage of the project"

N = 25	H1 (duration to trial of *civil* cases)	H3 (adoption in bordering countries)
Linear regression coefficient against *stage* ($p < 0.01$)	0.003 ($p < 0.01$, $R^2 = 0.28$)	8.051 ($p < 0.02$, $R^2 = 0.21$)
T-stat (df = 24)	3.206 ($p < 0.03$)	1.904 ($p < 0.04$)

4 Results

4.1 H1 and H3

We only find statistical significant results when considering the *stage* of the project; the other dependent variables did not result in statistically significant relations even if a Principal Component Analysis showed them as rather close together (see Fig. 2), notably with *stage* very close to the area of implementation. When controlling for quality of government and GDP per capita, none of them have a significant effect on the dependent variables.

Furthermore, and regarding H1, we only obtained statistically significant results when considering duration of civil trials (see Table 2) and using one-tail t-tests with the stage of the projects clustered into 2 groups. Duration to criminal and administrative trials did not result in statistically significant results (see in Appendix B Table 7), as well as a one-way ANOVA test was not statistically significant ($F = 1.946$, $p = 0.161$, df = 24).

Therefore, we can accept H1 and H3 within this set of conditions: the average number of days to trial in a country as well as the level of e-government adoption in neighboring countries both significantly influence a government's decision to start projects on AI in the judiciary.

4.2 H2

The survival function for the risk of starting an AI project obtained on $N = 28$ countries is shown in Fig. 3; the Cox's regression returns a statistically significant relation (coefficient = 0.277, $p < 0.01$).

We can therefore accept H2: left-leaning governments are more likely to start projects on AI in the judiciary. However, we did not find that the aim of the project (efficiency or accessibility) was statistically relevant to the likelihood of a left-wing (or right-wing) government to initiate an AI project in the judiciary (see Appendix B, Table 8).

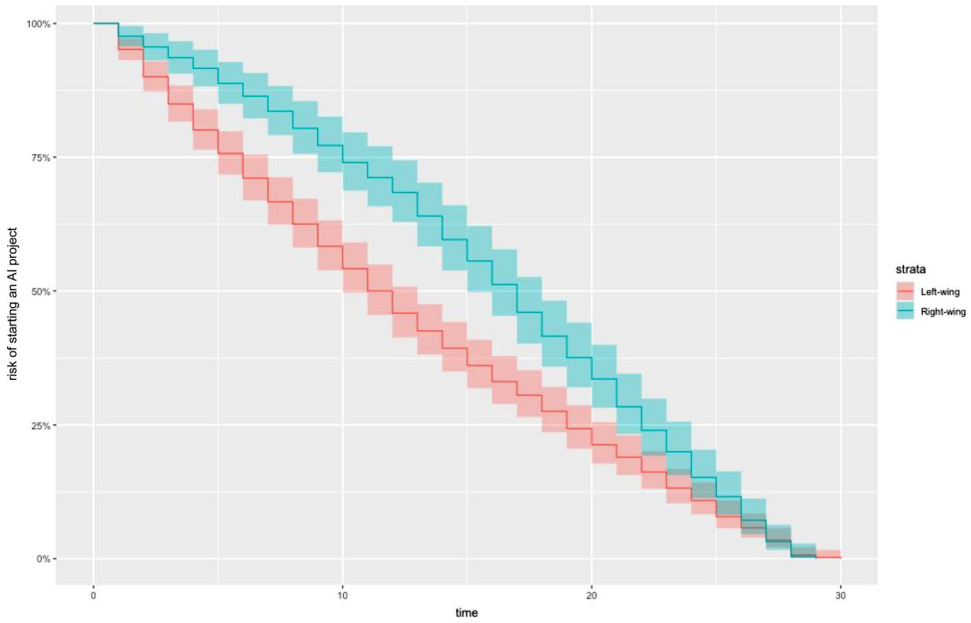


Fig. 3 The survival function shows a higher probability of projects being started from a left-wing government majority, and this constantly over time

5 Discussion

We can draw three conclusions from our analysis of the drivers behind the decision to implement AI in the judiciary in the context of advanced democracies. First, we find that the duration to trial of civil cases plays a role in deciding to turn to AI to alleviate the burden. More specifically, the average number of days to trial in civil cases for countries with an AI implementation averaged 310 whereas it averaged only 126 for those countries without implementation. This confirms the perception of the role of technology in relieving some of the burden on the state as it tries to find room to operate within existing constraints (financial resources, political capital).

Second, we find that the political orientation of the government in power does have an influence on starting AI projects in the judiciary, with left-wing governments more likely to do so than right-wing ones. Of the 23 countries with an implementation, only six were kickstarted by a right-wing government (Canada, Czech Republic, Estonia, France, Latvia, Switzerland) and 17 by a left-wing government (Austria, Croatia, Germany, Spain, Malta, Romenia, Slovenia, Denmark, Finland, Italy, Luxembourg, Netherlands, Poland, Portugal, Sweden, UK, USA). Also strengthening our conclusion is the observation that of the five countries without an implementation (Belgium, Cyprus, Hungary, Lithuania, Norway), all but one country (Hungary) did go through governments with a different majority across the 26 years under study. A closer look at the countries in our sample reveals no consistent pattern in socio-political or economic structures that would account for the observed variation. Both lists—those with and without AI initiatives in the judiciary—include a mix of social democracies and economically liberal states, centralised and federal systems, high- and low-GDP countries, large and small populations, as well as EU and non-EU members. This diversity suggests that these structural factors are unlikely to explain the observed difference. Instead, the pattern appears to align more closely with an ideological inclination, specifically a greater propensity among left-leaning governments to pursue such initiatives.

We therefore interpret this result in light of the agenda of left-wing governments to give more access to a country's residents to state services, even beyond the judiciary, regardless of the aim when starting the AI project. The mixture of projects started actually falls under both aims of making the state more efficient *and* to promote access to the law (e.g. with the single highest number of projects in the category of automatically anonymising court proceedings to publish them online, often explicitly to foster legal access), which explains why the addition of the aim as a treatment in the event history analysis did not play a role. Yet, we contend that even projects geared to make the judiciary more efficient contribute to a more responsive state, and hence to one that can better fulfil its promise and mandate towards its inhabitants.

Our third and last finding concerns the influence of neighbouring countries. As we have shown, countries with a judicial AI implementation exhibit, on average, a positive difference between their e-government index and their

neighbours' while countries without a judicial AI implementation exhibit, on average, a negative difference. In other words, those countries which have implemented judicial AI tools have generally a better readiness to implement access to public services via digital means, and those without lag behind their neighbouring peers when it comes to e-government.

6 Limitations and conclusion

In conducting this study, we have faced a number of methodological hurdles, probably due in no small part to the exploratory nature of the research question. With no clear framework to follow, and with no clear set of countries to focus on, we have iterated a number of times between frameworks, country sets, dependent/independent variables and data sources available before we could find meaningful and statistically relevant results (a few of the negative results of our investigation can be found in Appendix B). Our initial methodology was more traditional to comparative politics by picking three countries and qualitatively analysing them in-depth: two countries with judicial AI implementation, and a counter-case of a country without. However, by seeking to generalise the hypotheses to a larger *N*, we did not succeed. With this in mind, we would like to urge caution in the interpretation of our findings, notably when it comes to extrapolating them beyond the dataset of the countries considered.

Similarly, the results reported here have a certain number of limitations *per hypothesis* too. First regarding H1, we could not find any statistically significant result when looking at the waiting time to trial in the cases of criminal and administrative cases (even when trying with different statistical tools, from Pearson's correlation, to Principal Component Analysis, to one-way ANOVA). There might be a rationale explanation to this: when collecting the data, it has come to our attention that a few countries have explicitly referred to focusing on implementation of AI tools in the civil law domain, and it is hence sensical that we find this mirrored as to why they chose to focus on this sub-domain. Furthermore, countries' focus on civil rather than criminal cases, especially as a first foray to deploy AI tools in the judiciary may be explained by how resolving procedural issues or small claims is generally less sensitive than criminal proceedings [54, 55]. The higher stakes in criminal proceedings could therefore play a role, an argument which is also valid when looking at administrative justice where significant ethical and legal risks also arise, including concerns about the dehumanization of justice, real threats to the independence and impartiality of justice [56]. The many scandals which have arisen concerning using AI in public administration to make decisions quicker about social benefits (see from the Netherlands, to France, to the US [57]) appear to give credence to the argument about stakes at play—all the while highlighting the many pitfalls which exist when deploying AI tools in general [58] and in the judiciary in particular [59]. It remains that future qualitative studies using process tracing and (semi-) structured interviews with key decision-makers would be needed to confirm how the decision process was shaped.

Second, regarding H2, it may be argued that we only looked at the leaning of the majority in government as opposed to looking at the leaning of the minister of justice most likely in charge. The different datasets we considered (e.g. the Manifesto Project Dataset [60]) also did not include this information, and we accept that this may skew the results, albeit only to a certain limited extent. Also noteworthy concerning H2 is that we could not find any relation when running the historical event analysis with as additional covariate the aim of the project (efficiency/accessibility),we also found no relation when looking at odds-ratio and regressions. We cannot therefore conclude that the leaning of the party in government has an influence on the type of project started, and we can "only" fail to accept H2 without making a distinction for the aims of projects.

Lastly, regarding H3, we note that the operationalisation matters. We found no statistical significance in the following cases: when we only took the average (or standard deviation) between a country and its bordering neighbours' e-government index, when we took only the e-government index without consideration of neighbours (the e-government index is supposed to be a relative assessment of countries, not an absolute measure), or when we defined neighbours more coarsely in terms of sub-continent (Northern Europe, Northern America, etc.). While we posit that our current operationalisation is the one that makes the most sense (by looking at the difference, we actually look at how the country differs in relation to its neighbours), we also acknowledge the difficulty in the fragility of the conclusion dependent on the definition of the metric used to assess it.

Yet another challenge that we have experienced—on top of defining a subset of country and data availability—concerned the selection of the independent variable for a model. We started with a lot more hypotheses, but for the sake of coherence and shortness, we decided to present a model based only on the three hypotheses reported here. Other hypotheses for which we collected data and found no meaningful relations were: trust in AI, R&D spending, the degree

of access to AI expertise, regulation concerning AI in the judiciary, the independence and corruption of the judiciary, and distance to power. We notably acknowledge that our initial thinking was, if not that these variables correlate to some extent with AI adoption in the judiciary, that they might be otherwise confounding variables. For each of them, however, we have either found no relation worth reporting, or we faced challenges to match with our subset of countries at the intersection of our other datasets.

Despite these limitations, we still posit that the findings offer insights into AI adoption in the judiciary amidst the hype and craze that surrounds the topic of AI. By looking at data, we obtain different insights than what qualitative interviews can return on both adoption or non adoption [61] and offer a complementary picture. Whether decision-makers are aware that they follow certain drivers—be it on their perception of the state capacity as overburdened, of their own political party's agenda, or of how competitive they want to be against their neighbours—, the research teases out the relevance of the factors nonetheless. Future research could consider finding relations with further factors—although it may be well noted again to consider that we did not find any when looking at trust in AI, R&D spending, the degree of access to AI expertise, regulation concerning AI in the judiciary, corruption, independence of the judiciary, and distance to power. Regarding the wealth of possible factors playing a role (e.g. role of international organisations, trust in the police vs trust in the courts, etc.), and as already highlighted in the literature review section 2, there should not be a lack of material to collect and test.

Future research should also further investigate whether these findings apply to AI use in other branches of government, as current research in this area remains limited. For example, research on public perceptions of AI in policing indicates the influence of political partisanship: Republican members of the public tend to favor predictive policing over automated internal reviews, whereas Democrats show higher support for both [62]. Additionally, a few studies have similarly suggested how e-government initiatives could support AI adoption for crime management [63], and when fighting corruption and the shadow economy [64]. It would be valuable to further explore how a country's political ideology influences AI implementation in law enforcement—not only in the judiciary—and examine whether neighboring e-government initiatives similarly impact AI adoption. Investigating these factors across different government branches, such as policing, could offer deeper insights into the key drivers of AI adoption and the role of context in shaping policies.

Author contributions CG wrote the main manuscript and carried out the data analysis; VD and MH wrote the theory and hypotheses; CG and VD collected the data; ATM and SM gave directions to the research; all contributed to the conceptualisation of the research and all reviewed the manuscript.

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Data availability Data is publicly available and appropriate references to the data are provided within the manuscript.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

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Appendix A: List of countries

See Table 3.

Table 3 List of countries under analysis for each hypothesis

H1/H3	H2
Austria	Austria
Belgium	Belgium
Croatia	Canada
Cyprus	Croatia
Denmark	Cyprus
Estonia	Czech Republic
Finland	Denmark
France	Estonia
Germany	Finland
Hungary	France
Italy	Germany
Latvia	Hungary
Lithuania	Italy
Luxembourg	Latvia
Malta	Lithuania
Netherlands	Luxembourg
Norway	Malta
Poland	Netherlands
Portugal	Norway
Romania	Poland
Serbia	Portugal
Slovenia	Romania
Spain	Slovenia
Sweden	Spain
Switzerland	Sweden
	Switzerland
	United Kingdom
	USA

Appendix B: Summary of negative results

As exploratory research, we investigated a number of other relations (dependent and independent variables) which turned out to be either problematic or negative. Not to over-crowd the presentation of the main results, we report the results of this analysis only in this Appendix (Figs. 4, 5; Tables 4, 5, 6, 7, 8, 9).

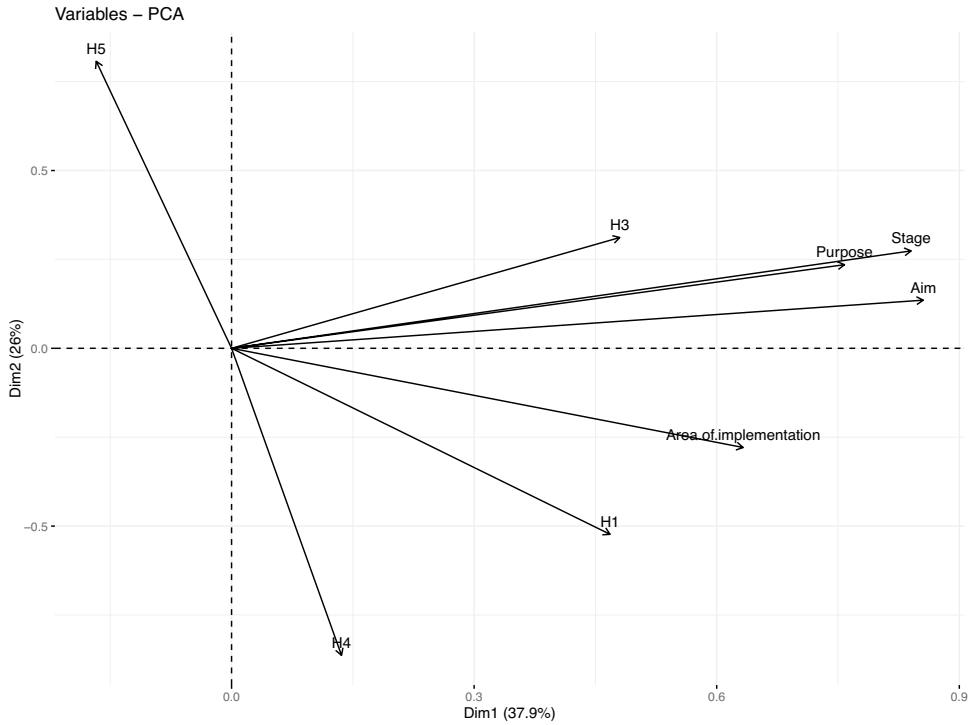


Fig. 4 Principal component analysis showing no correlation between the dependent variables and H4-H5 as they are orthogonal to one another

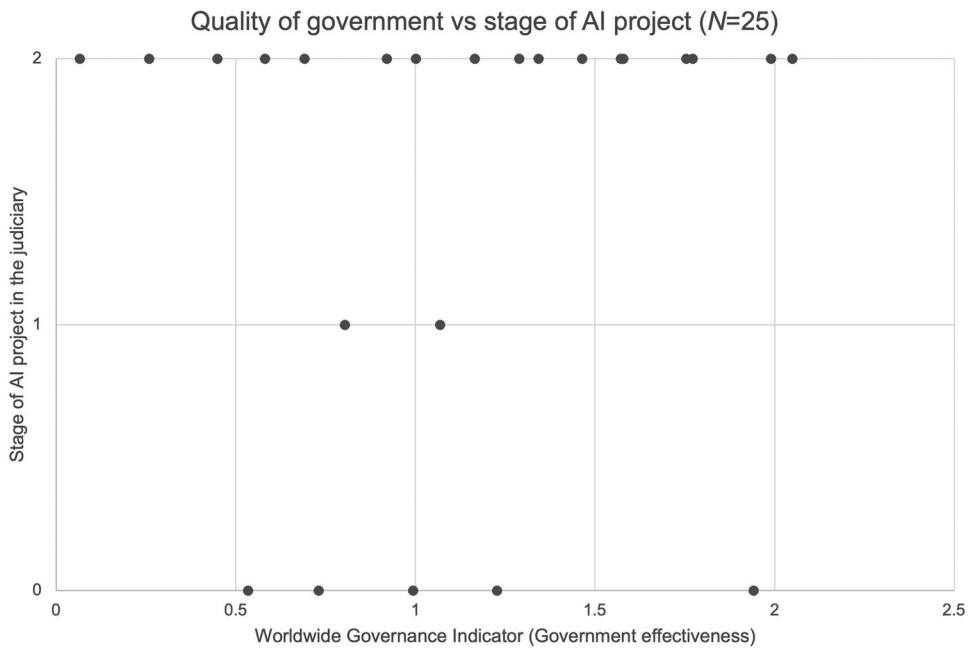


Fig. 5 Controlling for quality of government shows no effect (stage 0 = non-initiated, stage 1 = ongoing, stage 2 = implemented), with Pearson's correlation at 0.12 and p-value when regressing at 0.55

Table 4 Alternative hypotheses for which we ran into data issues when seeking to intersect for the country list with H1-H2-H3

Variable	Data source
Trust in AI	KMPG
R&D spending	OECD
Degree of access to AI expertise	Economist Intelligence Unit
Regulation concerning AI in the judiciary	Manual

Table 5 Alternative hypotheses and the t-stats results against the status of the project

H#	Hypotheses	Method of analysis	Data source	T-stat	p-value	df
H4	The distance to power impacts the decision to use AI in the judiciary	OLS	Hofstede	0.18875	0.42593	24
H5	The level of judicial independence and corruption impact the decision to use AI in the judiciary	OLS	Maplecroft/IHS	0.33828	0.36904	24

Table 6 Pearson's correlations with the dependent variables

	Year	Stage	Aim	Area of implementation	Purpose
H4	0.03283419	−0.1393671	−0.055295	0.27671811	−0.0281
H5	−0.0789893	0.03105127	0.0014733	-0.2814943	0.10653

Table 7 Statistically insignificant results of the one-tail t-test for two sub-categories within H1 against the stage of projects

N = 25	H1 Administrative cases	H1 Criminal cases
T-stat	0.640586	1.072671
p-value	0.263931	0.147043

Table 8 Result of Cox's regression when adding the aim of the project

	Coef	p
Political	0.27699	0.000515
Aim	0.02285	0.654135

Table 9 Odds ratio between political party and aim at 0.29 at CI = 0.7

# cases	Accessibility	Efficiency
Left wing	10	7
Right wing	5	1

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