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With AI through the energy crisis? Citizens' legitimacy perceptions of human and AI-supported hybrid decisions in an energy policy decision-making process

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ABSTRACT

Governments use artificial intelligence (AI) to support policy decisions, yet its democratic legitimacy remains contested. We examine public legitimacy perceptions of hybrid human-AI decision-making (HyDM) versus traditional human decision-making (HDM) in the siting of onshore wind power stations, a task made critical by Russia's full-scale invasion of Ukraine, which heightened the urgency of renewable deployment. In a preregistered online experiment with $n = 1205$ German citizens, we further investigate whether framing the energy transition as a security issue moderates the effect of decision-making type on legitimacy perceptions. While HDM was seen as slightly more legitimate in input aspects, there was no detectable difference in throughput or output legitimacy between HDM and HyDM. Framing the energy issue as a security threat showed no statistically significant moderation of these relationships. These findings provide arrangement-specific evidence on legitimacy perceptions of AI-supported decision-making in an energy-infrastructure context and highlight the role of public evaluations for the design of such decision-making processes.

Governments worldwide are increasingly experimenting with artificial intelligence (AI) tools to inform policy decisions, employing them to allocate welfare benefits, detect tax fraud, and plan critical infrastructure (Valle-Cruz et al., 2020). While proponents expect gains in efficiency and consistency, opponents warn that algorithmic decision-making can be perceived as undermining democratic legitimacy unless humans retain meaningful oversight and procedures remain transparent. Prior research shows that legitimacy perceptions of AI in political decision-making vary across contexts. Although several studies have examined these perceptions in high-stakes situations, there is limited evidence on how securitization, understood as framing an issue as an existential security threat, shapes such judgments. Thus, this article examines how citizens assess hybrid human-AI decision-making (HyDM) in comparison to traditional human decision-making (HDM) when the energy transition is framed as a security imperative. Russia's full-scale invasion of Ukraine in 2022, and the resulting sanctions and disruptions to Russian oil and gas supplies, have destabilised European energy markets. In response, Germany has aimed to accelerate the deployment of renewable sources, especially onshore wind power stations (WPS), thereby reducing its dependence on Russian gas and progressing toward climate neutrality (Federal Government of Germany, 2023; IPCC, 2023; Matthes et al., 2018). Determining suitable sites for new WPS, however, is fraught with legal challenges from environmental and civic groups, as well as intergovernmental conflicts between the states and the federal level (Kiunke et al., 2022).

Against this backdrop, AI has been proposed as a data-driven tool to support decision-makers in navigating the legal, administrative, and social hurdles that impede the rapid siting of new WPS. For example, AI tools could assist in coordinating and even automating the WPS siting process while incorporating relevant public interests, thus potentially making the process more efficient and expedited. Recent pilot projects, such as the research project WindGISKI (Reichert, 2022), explore AI systems to identify suitable locations for new WPS based on technical, geographical, ecological, economic, and social factors. Advanced Natural Language Processing (NLP) methods, for example, can be employed to discern citizens' concerns and include regional public opinion during

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the planning phase. Implementing such AI applications could give rise to new forms of hybrid decision-making wherein political decision-makers are supported by AI. However, introducing AI applications into the democratic political process must be approached with caution (König & Wenzelburger, 2020; König, 2022).

The success of partially automated HyDM systems may hinge on their functionality and their social acceptance by the population, particularly in comparison to the existing status quo of HDM. Political legitimacy is commonly understood to involve responsiveness to citizens who vote in a specific region (input legitimacy), fair and transparent procedures (throughput legitimacy), and favourable outcomes (output legitimacy) (Schmidt, 2013). However, a longitudinal representative survey in Germany reveals that only approximately 15% of respondents favour using AI in political decisions (CAIS, 2023). Yet, securitization theory posits that public support for extraordinary political measures, such as the use of AI, could increase if the issue is framed as a security threat (Balzacq et al., 2016). Consequently, two critical questions arise: First, to what extent does the application of AI influence the legitimacy of political decisions related to WPS siting? Second, in light of the current energy crisis, to what extent does framing the energy supply issue as a security threat affect the public's legitimacy perceptions of HyDM compared to HDM?

In a large preregistered online experiment ($n = 1205$), we examined the impact of decision-making types (HDM vs. HyDM) on perceived political legitimacy. Moreover, we tested whether framing the energy supply situation as a security threat moderates this effect. To do this, we drew on an existing pilot project that employed AI to determine WPS locations. Extending existing literature, our study situates legitimacy perceptions in a concrete and politically contested energy-infrastructure context and tests whether securitization framing linked to an energy crisis shapes evaluations of input, throughput, and output legitimacy. The results show that while HDM was perceived as slightly more legitimate on the input dimension, we found no difference between HDM and HyDM in perceived throughput or output legitimacy. Furthermore, we find no statistically significant evidence that a security frame increases the perceived legitimacy of HyDM relative to the human arrangement.

1. Leveraging AI applications for policy-making

Public administrations worldwide increasingly use data-driven tools and AI to inform routine decisions (Sousa et al., 2019; van Noordt & Misuraca, 2022). The motivations for this shift are often framed as straightforward. Adoption is often attributed to lower computing costs, political interest in "evidence-based" policies, and the perceived advantage of algorithms that can process information at a scale beyond human ability (Wirtz et al., 2021).

In China, an AI system scanned millions of Weibo posts and detected clusters of unusual pneumonia days before COVID-19 was officially confirmed (Shi et al., 2024). In Brazil, a robotic process automation tool was used to review public tenders and flag irregularities. This enabled auditors to focus on complex cases while routine checks ran in the background (Genaro-Moya et al., 2025). In Spain, the Catalan government has used AI to forecast the energy needs of municipal buildings and to prioritise retrofits expected to reduce emissions most effectively, helping translate climate goals into targeted investments (Cipriano et al., 2009).

These examples point to additional applications. Well-designed AI systems may detect early indicators that traditional monitoring might miss, simulate policy impacts before resources are committed, and reallocate personnel for tasks that require human judgment (Kulal et al., 2024). By identifying patterns across different datasets, governments may better align services with observed needs, whether by routing ambulances more efficiently, adapting job training, or targeting climate subsidies where they have the largest expected effect (Yar et al., 2024). Additionally, transparent AI models and follow-up audits may enhance accountability by documenting what evidence informed a decision (Genaro-Moya et al., 2025).

However, the use of AI in policy making can also backfire. Biased training data can reinforce discrimination, and complex or opaque models can make it difficult for civil servants or citizens to scrutinise outcomes (Kuziemski & Misuraca, 2020). The collection of large datasets also raises concerns about privacy and cybersecurity. Many agencies still lack the skills or infrastructure to assess sophisticated models (Genaro-Moya et al., 2025). Over-reliance on automated tools may weaken human judgment, and the cost of technical expertise can widen inequalities between well-resourced and underfunded administrations. Ultimately, when AI is perceived as displacing elected officials, concerns about technocracy and democratic legitimacy emerge (Haesevoets et al., 2024).

Thus, deploying AI in political decision-making differs in important respects from other domains. It requires democratic legitimacy. Political decision-makers derive their authority from citizens' electoral consent. Consequently, the use of AI in this domain must be evaluated not only in terms of decision outcomes but also in terms of how it affects citizens' perceptions of the legitimacy of democratic processes and results.

As governments weigh the potential benefits and risks of integrating AI into policymaking, they are increasingly focusing on areas where they expect the greatest value. Recent cross-country evidence suggests that AI development is associated with faster energy transitions, which helps explain why policymakers view AI as a strategic instrument for overcoming structural barriers in green energy deployment (Wang et al., 2026). One such area is environmental sustainability, where uptake is often motivated by the urgency of the issue and the availability of large volumes of relevant data (Elmousalami et al., 2025; Wang et al., 2025; Zhang et al., 2025).

2. The potential of AI applications for the siting of wind power stations in Germany

In Germany, dense settlement triggers frequent land-use conflicts that slow wind-power expansion. The 2022 "Wind-an-Land-Gesetz" (Wind-on-Land Act) therefore mandates that 2% of national territory host wind turbines by 2032, up from today's 0.5% (Federal Government of Germany, 2023). Public support is high in principle, as 81% of the German population favours faster expansion after Russia's full-scale invasion of Ukraine (Hofmann, 2022). Additionally, 50% of the population generally accepts onshore wind farms (Sonnberger & Ruddat, 2017). However, this acceptance rate declines to 35% when a wind farm is located within 500 m of the respondents' homes. Resulting lawsuits can stall projects, and concerns over impacts on people, wildlife, and landscapes vary regionally, which may undermine perceived legitimacy (Dehler-Holland et al., 2022; Kiunke et al., 2022; Rohe & Chlebna, 2021). Gaining social acceptance from citizens, particularly those residing near proposed WPS locations, is often viewed as important for the swift development of WPS (Hübner et al., 2023; Bell et al., 2013). Overcoming the existing challenges is crucial for accomplishing the country's renewable energy goals and mitigating the impact of energy crises.

Pilot projects have begun to deploy AI-supported land-analysis tools that rank sites (AMPERO, 2023). Systems such as WindGISKI combine geospatial and social data to recommend politically feasible locations, while studies investigate how AI can mine opinion data to guide policy design (Ceron & Negri, 2016; Valle-Cruz et al., 2020; Wirtz et al., 2018). Despite its potential, it is important to carefully consider potential effects on the perceived legitimacy of the political system when integrating AI applications into democratic decision-making processes. Failing to do so could be counterproductive, as new technologies may raise concerns about technocracy and democratic accountability.

3. The legitimacy of hybrid decision-making

Leveraging digital information systems to assist human decision-making in energy policy is not a new phenomenon (Gordon, 1985; Tahri, Hakdaoui, and Maanan, 2015). Evidence from the 2000s suggests that data analysis and modelling, such as environmental data mapping, depend on user perceptions (Díez & McIntosh, 2009). People tend to show a positive view of computer-based models in energy policy decision-making (Cockerill, Tidwell, and Passell, 2004). However, successfully integrating computer systems into environmental planning requires stakeholders to understand and endorse the new technologies (Hill et al., 2019). The introduction of AI systems into decision-making can pose a greater challenge, as they can automate and replace tasks previously executed by humans. Thus, the positive views of basic computer modelling for decision-making (Jankowski, 2009) do not necessarily translate to advanced AI-based methods. This points to the need for more in-depth research into citizens' perceptions of such technologies, and how to integrate them into democratic policy-making (Hagen, Harrison, and Dumas 2018; Ceron & Negri, 2016). Regarding potential hybrid forms of decision-making systems, König and Wenzelburger emphasize that “there are important fundamental considerations regarding when and how these applications can be compatible with democratic politics, and in what sense they can improve it” (König & Wenzelburger, 2021, 14).

Recently, a growing body of studies has addressed fundamental questions of AI acceptance in political decision-making (Araujo et al., 2020; Charles et al., 2022; König, 2022). Despite the increasing attention, the field has yet to establish a coherent theoretical framework, consistent empirical methodologies, and comprehensive insights into how HyDM affects perceived legitimacy. A legitimate decision must consider the opinions of the population (input legitimacy), implement effective and transparent procedures (throughput legitimacy), and produce effective results (output legitimacy) (Schmidt, 2013; Schmidt, & Wood, 2019; Scharpf, 1999). However, AI potentially erodes citizens' perceived legitimacy (Starke & Lünich, 2020): (a) In the input dimension, citizens may doubt having an influence on which criteria and data the AI uses for its decision. (b) Throughput legitimacy could be weakened because laypersons may struggle to understand the complex computational models. (c) Finally, output legitimacy could be compromised because citizens may question whether AI can produce better decisions compared to humans or that it could decide against the individual's own predicted outcome.

Empirical evidence from several studies demonstrated a preference for HyDM over fully automated decision-making (ADM) solely made by AI (Bigman and Gray, 2018; Starke & Lünich, 2020; Zhang et al., 2021). Even though the implementation of political ADM is highly unlikely in democratic societies, the existing literature remains valuable for informing our research questions and hypotheses, particularly given the scarcity of empirical studies comparing HDM and HyDM. AI can impact input legitimacy of policy decisions in multiple ways. First, access to Big Data raises privacy concerns among citizens (Agarwal, 2018; Ohm, 2010). Second, numerous studies suggest biases resulting from low-quality training or input data (Caliskan et al., 2017; Sühr et al., 2021). Consequently, minorities and socially disadvantaged groups face the risk of marginalization because they are often underrepresented in digital data. Due to such biased data, algorithms may perpetuate and even amplify structural biases in their decisions (Barocas and Selbst, 2016; Miller and Keiser, 2021; Woodruff et al., 2018; Žliobaitė, 2017).

In the context of WPS, individual residents are disproportionately affected by the drawbacks of wind power expansion, whereas the majority of society benefits from the increased energy supply. The marginalization of residents in digital data may pose a significant risk when using HyDM. Existing research approaches deploy *opinion mining* to analyze data from social networks, enabling them to identify citizens' preferences within specific regions and incorporate them into decision-making processes (Ceron & Negri, 2016; Sluban & Battiston, 2017). However, previous studies indicated that such indirect participation methods do not enhance input legitimacy (Starke & Lünich, 2020; Waldman & Martin, 2022). HyDM poses a risk of bypassing democratic procedures within the decision-making process, as it may lack consultation with elected institutions or citizens during the process (Starke et al., 2022). Furthermore, unlike HDM processes, public debates that could enhance the comprehensibility and transparency of the decision are often absent. Waldman and Martin (2022) assert that decisions based on general data available on the internet are perceived as less legitimate compared to those based on data gathered specifically for the intended purpose. Taken together, these findings suggest that the data foundation of an algorithmic decision system has low legitimacy, leading to the formulation of the following initial hypothesis concerning input legitimacy.

H1. HDM is perceived to have higher input legitimacy in political decisions about land designation for new wind power stations than HyDM.

Additionally, the complexity of algorithmic processes can be challenging for laypeople to understand (Fine, & dede Fine Licht, 2020). A representative survey conducted in Germany revealed that only 15% of respondents supported the use of AI in political decision-making (CAIS, 2023). However, Starke and Lünich (2020) found no difference between HDM and HyDM when examining throughput legitimacy in a scenario involving the European Commission's application of AI in decision-making. A widely studied aspect of throughput legitimacy is the perception of fairness in algorithmic decision systems. While some authors argue that AI decisions are perceived as fairer than human decisions (Helberger et al., 2020; Marcinkowski et al., 2020), others found the opposite (Acikgoz et al., 2020; Harrison et al., 2020; Lee and Rich 2021; Newman et al., 2020). Still, other studies reported no significant difference in fairness perceptions between HDM and ADM (Plane et al., 2005; Suen et al., 2019).

Regarding HyDM, Nagtegaal (2021) found that in high-complexity situations, decision-making systems involving humans and algorithms are perceived as fairer compared to ADM and HDM. However, Newman et al. (2020) concluded that HDM was rated higher than HyDM. From this inconclusive research landscape, we infer that people's perceptions are likely influenced by the context of the respective use case (Starke et al., 2022). Given the ambivalent research findings, we refrain from formulating a hypothesis for throughput legitimacy and instead pose the following research question.

RQ1. Do perceptions of throughput legitimacy of political decisions about land designation for new wind power stations differ between HDM and HyDM?

Two notions of output legitimacy can be distinguished. The first dimension refers to the perceived achievement of the goal, while the second captures the favourability of the decision made in pursuit of said goal. AI-based systems are often anticipated to make decisions more efficiently, reliably, and objectively than human decision-makers (Bansak et al., 2018; Poel et al., 2018; Rieder and Simon 2016; Sousa et al., 2019). On the one hand, Ingrams et al. (2022) found that when ADM is employed in the U.S. Internal Revenue Service, AI is perceived as more competent. On the other hand, Starke and Lünich (2020) revealed no difference in perceived goal achievement when comparing HyDM and HDM. As this study largely builds upon the research design of Starke and Lünich (2020) and also investigates a HyDM process, we propose the following hypothesis.

H2. Perceived goal achievement does not differ between HDM and HyDM in political decisions about land designation for new wind power stations.

While algorithmic systems offer numerous benefits, they can also produce erroneous decisions or, at the very least, decisions that citizens view as unfavourable. Several studies indicate that individuals who disapprove of a judicial decision tend to assign less legitimacy to the court or judge (Bartels and Johnston, 2013; Christenson and Glick, 2015; Badas, 2019). Furthermore, Waldman and Martin (2022) found that human mistakes lead to more significant losses in legitimacy perception compared to algorithmic mistakes. In contrast, the concept of algorithmic aversion suggests that people are less inclined to delegate a decision to an algorithm if it has previously made a poor choice (Dietvorst et al., 2018). Research by Ingrams et al. (2022) also shows that human decisions are perceived as more sincere and benevolent. Moreover, Starke and Lünich (2020) found no difference in evaluating the favourability of the decision between HDM and HyDM. As this study also examines a hybrid decision-making process, where human decision-makers make the final decision, we base our hypothesis on findings by Starke and Lünich (2020).

H3. The favourability of the decision does not differ between HDM and HyDM in political decisions about land designation for new wind power stations.

4. Securitization as a framing process

The energy crisis resulting from Russia's full-scale invasion of Ukraine that began in 2022 sparked a societal discussion about energy transition in Germany. The challenges posed by scarce and more expensive energy imports for Germany were widely perceived as a threat to stability and national security. Buzan et al. (1998, p. 21) argue that "the special nature of security threats justifies the use of extraordinary measures to handle them".

Grounded in the securitization theory of the Copenhagen School, a social issue becomes a security threat not due to its inherent characteristics but because it has been framed as such by political actors (Buzan et al., 1998; Wæver, 1995; Balzacq et al., 2016). Buzan et al. (1998) understand security as a discursive construct applicable to various policy domains. The authors posit that securitization begins as a speech act, wherein an actor presents a problem as a security threat to a certain reference object. Successful securitization occurs when the audience accepts the depiction of an existential threat and legitimizes the extraordinary measures taken to address it. Buzan et al. (1998) characterize extraordinary measures as those that bypass democratic rules and procedures. Grauvogel and Diez (2014) propose understanding the theory of the Copenhagen School for empirical analyses as a framing process. According to Entman (1993), framing entails the following:

"To frame is to select some aspects of a perceived reality and make them more salient in a communicating text, in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation for the item described."

Some political actors in Germany, indeed, framed the energy crisis amid Russia's full-scale invasion of Ukraine as a security issue and a threat to national security. We argue that securitization framing may moderate the effect of decision-making type (HDM vs. HyDM) on the perceived input, throughput and output legitimacy of political decisions. Conceptually, securitization framing may first shift citizens' subjective threat appraisal by increasing perceived urgency and stakes. This first-stage shift can change which evaluative criteria citizens prioritise when judging decision-making arrangements. One logic emphasizes necessity: urgency increases the salience of rapid, effective problem-solving, which can raise willingness to delegate to expert and technical systems and reduce the relative weight of participatory input and procedural constraints. A second logic emphasizes accountability: high stakes heighten demands for identifiable responsibility, transparency, and contestability, which can reduce acceptance of AI-supported arrangements if they are perceived as diluting accountability. Accordingly, securitization can attenuate or amplify differences between HDM and HyDM across input, throughput, and output legitimacy depending on which evaluative logic dominates. Building on these two evaluative logics (necessity vs. accountability), we derive two plausible and competing moderation pathways. Under a *necessity-based* logic, perceiving a threat to national security may increase citizens' acceptance of HyDM. This line of reasoning follows the argument put forth by Buzan, which suggests that extraordinary challenges require extraordinary measures to resolve them. Empirical evidence reinforces this argument. In experimental settings, participants were more likely to accept algorithmic recommendations when operating in unpredictable environments, suggesting that perceived threat and uncertainty can increase support for automated decision-making (Sutherland et al., 2016). Although overall acceptance of ADM is low in morally sensitive or consequential scenarios, individuals who felt a stronger need for leadership were more open to algorithmic support, indicating that the authority of a securitizing actor can legitimize ADM in times of crisis (Utz et al., 2021). Perceptions of fairness also vary by context: ADM was viewed as fairer than human decision-making in high-impact areas such as health and justice, where decisions carry significant consequences (Araujo et al., 2020). Likewise, hybrid decision-making was perceived as particularly fair in complex scenarios (Lee et al., 2019), suggesting that combining human and algorithmic input may be more suitable for intricate policy problems, such as energy security. Together, these findings indicate that securitization framing may shape public acceptance of HyDM by increasing perceptions of urgency and complexity.

Under an *accountability-based* logic, high perceived stakes may increase preferences for human responsibility and control, leading citizens to favour HDM over HyDM. Several studies have shown that people prefer human advisors over algorithms in volatile or high-risk situations, such as financial decisions or demand forecasting under high-profit conditions (Zhang et al., 2021; Feng & Gao, 2020). Similarly, Nagtegaal (2021) reports that HDM was perceived as fairer than ADM in high-complexity decisions, as humans were considered better equipped to adapt to unique circumstances. Additionally, in situations marked by high uncertainty, such as medical decisions or election forecasts, algorithms are often rejected in favour of human decision-makers (Dietvorst, & Bharti, 2020; Kawaguchi, 2021). In legitimacy terms, necessity-based reasoning may increase tolerance for reduced input and procedural demands while strengthening output-oriented evaluations, whereas accountability-based reasoning may increase the salience of input and throughput criteria (voice, transparency, contestability) under high stakes.

These competing perspectives suggest that securitization framing may moderate the effect of decision-making type on perceived legitimacy. At the same time, they highlight the inconclusive nature of empirical findings in this area. Given the ambiguity in prior research, we do not formulate directional hypotheses. Instead, we propose the following exploratory research questions to examine how the type of decision-making and securitization framing interact across the three dimensions of legitimacy.

RQ2. Does exposure to a security frame moderate the relationship between decision-making type and perceived input legitimacy in political decisions on land designation for new wind power stations?

RQ3. Does exposure to a security frame moderate the relationship between the type of decision-making and the throughput legitimacy of land designation for new wind power stations?

RQ4. Does exposure to a security frame moderate the relationship between decision-making type and perceived goal achievement in political decisions about land designation for new wind power stations?

RQ5. Does exposure to a security frame moderate the relationship between the type of decision-making and the favourability of the political decision about land designation for new wind power stations?

For an overview of the research questions and hypotheses, see Fig. 1.

5. Method

To test the research questions and hypotheses, we conducted an experimental survey using a 2x2 between-subjects design. Respondents were consequently randomly assigned to one of four conditions.

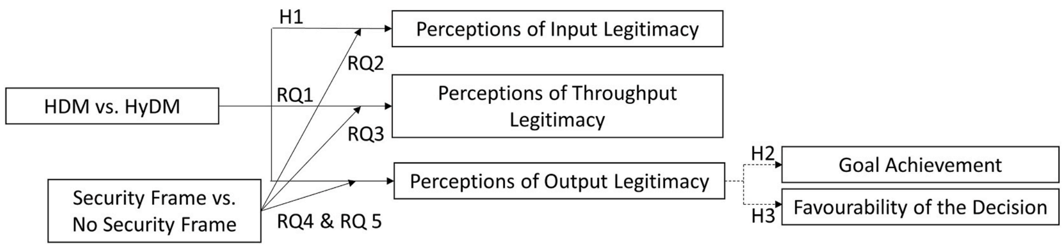

Fig. 1. Conceptual model with hypotheses and RQ

Although a 2x2 ANOVA is a common analysis for factorial experiments, our outcomes are modeled as latent constructs measured by multiple items. We therefore used SEM to estimate experimental effects on latent legitimacy dimensions while accounting for measurement error. The structural part of the model corresponds to the general linear model underlying a factorial ANOVA (main effects and interaction), with the advantage that outcome measurement is explicitly modeled. Data analysis was conducted using the statistical program R (Version 4.2.1), employing structural regression modelling with the lavaan package. The preregistration of the hypotheses and research questions, as well as the data collection instrument, can be accessed online (https://osf.io/2wbd3/overview?view_only=c79b844fec61404cb4c233e7ee9ecfff). Deviations from the preregistration are documented in the supplementary information (SI).

5.1. Sample

Respondents were recruited by the panel provider Respondi, which is certified according to the ISO standard 20252:2019 for social science research. The survey was conducted via an online questionnaire using the SoSci Survey web application from July 22 to August 3, 2022. To avoid overrepresentation and skew in the sample composition, quotas were used as stopping rules. The sample was composed according to population-representative quotas in terms of age, gender, and educational level (Eurostat. 10.09, 2022). A total of 1339 respondents successfully completed all questions. After filtering for respondents who failed the attention check and who completed the questionnaire too quickly (RSI >2, see Leiner (2019)), the final sample consisted of n = 1205 respondents.

The average age was 47.62 (*SD* = 15.36). Altogether, 634 (52.6%) respondents identified as women, 567 (47.1%) as men, and 4 (0.3%) indicated a diverse gender. Further, 386 (32.2%) respondents reported basic educational attainment, 404 (33.8%) reported medium educational attainment, and 407 (34%) reported higher educational attainment.

5.2. Procedure and survey design

Before the experimental manipulation, all participants were provided with a short neutral introduction to the general concept of AI. This introduction explained how AI systems process large datasets, learn to identify patterns, and generate recommendations or decisions (see Appendix B in the SI). The purpose of this introductory text was to ensure a common baseline of understanding and reduce variance in individual interpretations of AI prior to exposure to the stimulus materials.

5.2.1. Treatment conditions (independent variable)

Respondents received a short text (ca. 250 words per condition) about the decision-making process regarding the siting of WPS. The stimuli manipulated the independent variable *type of decision-making,* and the moderator variable *security framing.* We used them as dummy variables in the data analysis: HDM (0) vs. HyDM (1) for decision-making, and absence (0) vs. presence (1) of a securitization frame (see SI for more details).

HDM vs. HyDM The type of decision-making manipulation differentiates between HDM and HyDM. The HyDM condition represents a decision-making process in which an AI proposes suitable wind power locations. These proposals ultimately require approval by human decision-makers from the authorized regional regulatory body. The brief text elaborates on the data used in the decision-making process, drawing on real-world examples. Importantly, the AI system in the vignette incorporates not only technical and geographical indicators but also data related to citizen acceptance and local demographic characteristics. The HDM condition describes the decision-making involving a citizens' council. In this case, the citizens' council pre-selects areas for new WPS, which are also ultimately approved by human decision-makers from the regulatory authority. The described model of citizens' councils is based on a participatory concept from Baden-Württemberg (Forum Energiedialog Baden-Württemberg, 2019). To present a realistic comparison, both conditions were designed to integrate citizens' opinions into the decision-making process, albeit through different mechanisms (direct deliberation versus data-driven acceptance indicators). Thus, the two arrangements differ not only in the presence of AI but also in how participation is structured. Accordingly, our design does not isolate a "pure" AI effect. Rather, it compares two institutional configurations that reflect plausible real-world implementations of HDM vs. HyDM.

Presence vs. Absence of a Securitization Frame To manipulate the presence vs. absence of a securitization frame, we draw on the three criteria suggested by the Copenhagen School (security grammar, authority and threat associated with the security sector) and the frame components introduced by Entman (1993) (problem definition, moral evaluation, causal interpretation, proposed solution). The following quote from the Federal Minister of Economics, Robert Habeck, serves as a securitizing speech act in the stimuli:

"It is thus evident that the dispute over energy is a weapon and that energy can be used harshly in an economic conflict …. The prerequisite for us to be energy secure in the future is the expansion of renewable energies" (Habeck, 2022, min. 1:00 – min. 1:33).

The use of security grammar is evident in the description of the existential and irreversible threat of economic conflict and the use of energy as a weapon. The authority of the security framing actor is plausible, as Federal Minister of Economics Robert Habeck was the highest-rated German politician in terms of likeability and performance during the survey period from July 22 to August 3, 2022 (Forschungsgruppe Wahlen, 2022). Finally, security framing identifies characteristics traditionally associated with the security sector through expressions such as "economic conflict", "confrontation", "weapon", and "energy secure".

The manipulation results in four experimental conditions with the following characteristics.

1. HyDM and securitization (condHyDM/S)
2. HDM and securitization (condHDM/S)
3. HyDM and no securitization (condHyDM/NoS)
4. HDM and no securitization (condHDM/NoS)

5.2.2. Manipulation check

We used three items (1 = does not play a part, 5 = does play a major part) to test whether participants perceived the differences between the conditions. We estimated separate ANOVA models using the Games-Howell post hoc test.

First, respondents answered the question: *What part do technical applications play in the decision-making process?* The results ($F(3, 663.67) = 26.31$, $p < 0.001$) indicated that condHyDM/S ($M = 3.60$; $SD = 0.75$) and condHyDM/NoS ($M = 3.64$; $SD = 0.85$) differed significantly from condHDM/S ($M = 3.18$; $SD = 0.97$) and condHDM/NoS ($M = 3.16$; $SD = 0.93$). Thus, respondents recognized that the decision-making processes were technically automated to varying extents.

Second, respondents answered the question: *What part do different interest groups (e.g., politicians, residents, investors) play in the decision-making process?* The results ($F(3, 1201) = 8.741$, $p < 0.001$) indicated that condHyDM/S ($M = 3.61$; $SD = 0.87$) and condHyDM/NoS ($M = 3.66$; $SD = 0.83$) differed significantly from condHDM/S ($M = 3.9$; $SD = 0.81$) and condHDM/NoS ($M = 3.84$; $SD = 0.82$). Thus, respondents recognized that humans were involved in the decision-making process to varying extents.

Third, respondents answered the question: *What part does a national security threat play in the decision-making process?* The results ($F(3, 1201) = 31.16$, $p < 0.001$) indicated that condHyDM/S ($M = 3.30$; $SD = 1.14$) and condHDM/S ($M = 3.43$; $SD = 1.06$) differed significantly from condHyDM/NoS ($M = 2.74$; $SD = 1.05$) and condHDM/NoS ($M = 2.78$; $SD = 1.14$). Thus, respondents recognized the conditions that emphasized the threat to national security to varying extents. As a manipulation check, this item captures whether respondents registered the vignette's security reference (i.e., perceived salience), but it does not directly measure subjective threat appraisal or felt urgency to act. At the same time, the mean in the no-securitization conditions remained close to the scale midpoint. This observation suggests that, in the survey context, many respondents perceived a non-trivial baseline security relevance even without the securitizing cue, which likely attenuated the effective contrast between conditions.

One limitation of empirical research on the legitimacy perceptions of ADM is that "decision-making arrangements tested here are hypothetical and are unlikely to be implemented in the immediate future" (Starke & Lünich, 2020, p. 14). Since the situation presented in this study has only been planned and tested, but not yet been implemented, we tested whether respondents perceived the scenario as realistic. Consequently, respondents answered the question *How realistic do you think the decision-making process is?* The results indicated no significant difference among the four conditions ($F(3, 1201) = 0.91$, $p = 0.435$). The mean value for all conditions was above the midpoint of the scale, suggesting that, on average, respondents assessed the depicted scenario as realistic.

5.3. Randomization checks

Before running the analyses, we conducted a series of randomization checks to verify the distribution of age, gender, education, and the preference for human vs. AI-based decision-making authority in wind power planning. Randomization checks indicated balanced distributions across conditions (see SI).

5.3.1. Measures

All dependent and control variables were translated from English to German and assessed using five-point Likert scales, ranging from 1 (do not agree at all) to 5 (fully agree). The exact wording of all items is summarized in Appendix E in the SI.

The dependent variables (DV) were adopted from Starke and Lünich (2020) and measured *input legitimacy* (DV1), *throughput legitimacy* (DV2), and for *output legitimacy*, the dimensions of *perceived goal achievement* (DV3) and *favourability of the decision* (DV4). All items in each scale were randomly rotated and used as indicators of a latent variable in the analysis.

Input Legitimacy (DV1). The following three items were used to measure perceived input legitimacy.

- People like me could influence the decision-making process.
- People like me were able to contribute their opinions to the decision-making process.
- All citizens had the opportunity to participate in the decision-making process.

Throughput Legitimacy (DV2). Perceived throughput legitimacy was measured with three items. The item stem read: "The decision-making process described was …" Respondents then rated the extent to which they perceived the process as (a) *fair*, (b) *satisfactory*, and (c) *appropriate.*

Goal Attainment (DV3). Perceived goal attainment was measured with three self-developed items. Respondents were introduced to this block as follows: "Now it is about your personal assessment of whether the decision-making process you have just read is suitable for achieving the overarching goals. To what extent do you agree with the following statements?" They then evaluated whether the decision-making process would contribute to (a) a stronger expansion of wind turbines in Germany, (b) guaranteeing the energy supply in Germany, and (c) achieving a fair compromise between wind power expansion and local residents, as well as environmental and nature conservation.

Decision favourability (DV4). Decision favourability, as the second component of output legitimacy, was measured with three items. Respondents were introduced to this block as follows: "In the following, we are interested in your personal opinion on the decision to expand wind turbines, which you have just read about. To what extent do you agree with these statements?" They then indicated their agreement with the statements (a) "I accept the decision," (b) "I agree with the decision," and (c) "I am satisfied with the decision."

Before conducting a group comparison via latent factor modelling, we assessed measurement invariance of the indicators using a sequential approach (Putnick & Bornstein, 2016). Configural invariance was initially verified (M1), followed by metric (M2) and scalar invariance (M3) tests, using chi-square difference and CFI deviation criteria (Cheung & Rensvold, 2002). Lastly, residual invariance was tested (M4). Table 1 confirms strong factorial invariance, satisfactory internal consistency, and adequate convergent validity. Thus, all subsequent structural regression models employed equality constraints for factor loadings and intercepts.

5.3.2. Control variables

To control for potential confounding factors in our analysis model, we measured age, gender, and educational attainment using standard single-item measures. We further inquired about respondents' *trust in politicians*, *trust in AI*, and *attitudes towards wind power* (1 = do not agree, 5 = do agree).

Trust in Politicians. Trust in politicians was measured using four items adopted from Lünich and Kieslich (2022) (e.g., *I trust politicians to make the right decisions.*). The items show good reliability (Cronbach's α; = 0.95) and adequate convergent validity (Average Variance Extracted (AVE) = 0.83).

Trust in AI. Trust in AI was measured using four items adopted from Shin (2021) and Lünich and Kieslich (2022) (e.g., *Decisions made by AI are trustworthy.*). The items show good reliability (Cronbach's α; = 0.96) and adequate convergent validity (AVE = 0.84).

Attitudes towards wind power. Attitudes toward wind power were measured using eight items adopted from Meyerhoff et al. (2008) (e.g., *Living within sight of wind turbines would not bother me.*). The items showed satisfactory internal consistency (Cronbach's α; = 0.68) but insufficient convergent validity (AVE = 0.22). Therefore, only three items were used for the measurement (see Appendix in the SI for details), which showed similar reliability (Cronbach's α; = 0.64) but improved convergent validity (AVE = 0.37).

6. Results

In this study, we employed effect coding for factor scaling, a

Table 1
Measurement invariance legitimacy.

	Chisq (df)	CFI	RMSEA	comp	Chisq diff (df)	CFI diff	RMSEA diff
M1: Configural Invariance rowhead	465.00*** (192)	0.977	0.069 (0.061-0.077)				
M2: Metric Invariance rowhead	495.70*** (216)	0.976	0.066 (0.058-0.073)	M1	30.70 (24)	−0.001	−0.003
M3: Scalar Invariance rowhead	544.25*** (240)	0.974	0.065 (0.058-0.072)	M2	48.55** (24)	−0.002	−0.001
M4: Residual Invariance rowhead	628.85*** (276)	0.97	0.065 (0.058-0.072)	M3	84.60*** (36)	−0.004	<0.001

procedure that "constrains the set of indicator intercepts to sum to zero for each construct and the set of loadings for a given construct to average 1.0" (Little et al., 2006, p. 62). To facilitate interpretation, we report condition-specific mean estimates and provide a corresponding visualization with confidence intervals. Table 2 presents the model-implied latent means for input legitimacy, throughput legitimacy, goal attainment, and decision favourability separately for each experimental condition, and Fig. 2 visualizes these estimates with 95% confidence intervals. To test the hypotheses and research questions, a hierarchical structural linear regression model was estimated (see Table 3). First, the experimental condition regarding the type of decision-making was used as an independent dummy variable in Model 1, where the four distinct legitimacy variables served as latent dependent variables. Second, the second experimental condition of securitization was also added as a dummy variable to Model 2, along with the interaction effect. Eventually, a third model includes the control variables.

6.1. Perceived input, throughput and output legitimacy

To test H1-H3 and RQ1, the first structural regression model was estimated (see Model 1, Table 3). The model shows acceptable fit ($\chi^2(56) = 310.37$, $p < 0.001$; $RMSEA = 0.06$ $CI[0.05, 0.07]$; $CFI = 0.98$). The results indicate a small significant effect of the type of decision-making on the input legitimacy (b= 0.23, $SE = 0.06$, $p < 0.001$, $\beta_{\text{standardized}} = 0.12$). Input legitimacy was lower in the condition of HyDM than in the condition of HDM when it comes to the political decision about land designation for new WPS. Accordingly, H1 is supported. In response to RQ1, the results show that perceptions of throughput legitimacy in the political decision about land designation for new WPS did not differ between HDM and HyDM. With regard to the two forms of output legitimacy, we find no statistically significant differences in expected goal attainment or decision favourability between the HDM and HyDM scenarios. Accordingly, H2 and H3 are supported.

6.2. Securitization

We investigated four moderation effects (RQ2, RQ3, RQ4, and RQ5) using the second structural regression model (see Model 2 in Table 3). The model shows acceptable fit ($\chi^2(72) = 335.58$, $p < 0.001$; $RMSEA =$ 0.06 $CI[0.05, 0.06]$; $CFI = 0.98$). Our results show no statistically significant effect of the security frame on perceived legitimacy in the WPS siting scenario. Moreover, the security frame does not significantly moderate the difference between HDM and HyDM on any legitimacy outcome. We find no statistically significant interaction between security framing and decision-making type on any legitimacy outcome, including input legitimacy (RQ2). This finding suggests that input-legitimacy evaluations did not differ across decision-making types as a function of the security frame. In response to RQ3, we find no statistically significant interaction between security framing and decision-making type for throughput legitimacy. Accordingly, people's evaluations of legitimacy remain consistent, regardless of the security threat. Similarly, in response to RQ4, we find no statistically significant interaction for expected goal attainment. Thus, there is no evidence that the security frame increases expected goal attainment differently for HDM versus HyDM. Lastly, in response to RQ5, we find no statistically significant interaction between security framing and decision-making type for decision favourability. The presence of a security threat does not change people's equal evaluation of the favourability of decisions made by either HDM or HyDM.

6.3. Influence of control variables

We subsequently incorporated key control variables into our structural regression model (refer to Model 3, Table 3) to assess the impact of trust in politics and AI, attitudes towards wind power, and sociodemographic factors (age, gender, and educational attainment) are associated with the dependent variables and alter the relationships between our primary independent variables and the outcomes. This inclusion helps us control for potential confounding factors that could affect the outcome, while improving the overall accuracy and explanatory power of our regression model. To account for possible interactions between trust variables and the stimulus, corresponding interaction terms were added to Model 3. The model shows acceptable fit ($\chi^2(814) = 1857.74$, $p < 0.001$; $RMSEA = 0.03$ $CI[0.03, 0.04]$; $CFI = 0.97$). The findings demonstrate that the main conclusions concerning the effects of our stimuli remain robust. The relationships and absence of relationships between the primary independent variables and the dependent variables persist after the introduction of the control variables. This persistence strengthens our confidence in the conclusions derived from the experiment. Trust in politics, trust in AI, and attitudes toward wind energy are each positively associated with the legitimacy outcomes, indicating that respondents who report higher baseline trust and more favourable wind-energy attitudes perceive greater legitimacy across conditions. The interaction between the type of decision-making and trust in AI is negative and statistically significant for throughput legitimacy and decision favourability, but not significant for input legitimacy or goal attainment, which means that the association of trust in AI with the outcome is weaker under HDM than under HyDM for the significant outcomes.

7. Discussion

This study set out to investigate perceived input, throughput, and output legitimacy of two different political decision-making arrangements, one involving only human decision-makers and one in which human decision-making is supported by AI systems. Because our vignettes contrast two decision-making arrangements that differ in both algorithmic support and the salience of participatory input (citizens' council vs administrative process), differences, especially in input legitimacy, should be interpreted as arrangement effects rather than as an isolated AI effect. Additionally, we examined whether framing energy security during Russia's full-scale invasion of Ukraine as a national security issue moderates these evaluations. We first discuss the main effects of the type of decision-making (H1–H3, RQ1) and then turn to the interaction effects of securitization framing (RQ2–RQ5).

7.1. HDM marginally trumps HyDM

The empirical findings from our factorial survey are broadly consistent with previous research. HDM is perceived as more legitimate on the input dimension, which refers to citizens' opportunities to participate and voice their concerns. In this respect, HyDM receives lower ratings. Taken at face value, this could suggest that citizens do not see clear potential in AI to enhance participation, even though AI-based

Table 2
Means legitimacy.

Latent Factor	C1 HyDM/ Sec: Estimate	C1 HyDM/ Sec: SE	C1 HyDM/ Sec: CI LL	C1 HyDM/ Sec: CI UL	C2 HDM/ Sec: Estimate	C2 HDM/ Sec: SE	C2 HDM/ Sec: CI LL	C2 HDM/ Sec: CI UL	C3 HyDM/ NoSec: Estimate	C3 HyDM/ NoSec: SE	C3 HyDM/ NoSec: CI LL	C3 HyDM/ NoSec: CI UL	C4 HDM/ NoSec: Estimate	C4 HDM/ NoSec: SE	C4 HDM/ NoSec: CI LL	C4 HDM/ NoSec: CI UL	Cronbach's Alpha	Average Variance Extracted
Input Legitimacy	2.789	0.054	2.683	2.895	3.041	0.061	2.922	3.160	2.762	0.060	2.644	2.879	2.979	0.054	2.874	3.085	0.884	0.722
Throughput Legitimacy	3.155	0.046	3.064	3.246	3.196	0.052	3.095	3.298	3.093	0.053	2.988	3.198	3.075	0.049	2.980	3.171	0.912	0.779
Goal Attainment	3.501	0.045	3.414	3.588	3.508	0.045	3.419	3.597	3.422	0.047	3.330	3.514	3.402	0.043	3.317	3.486	0.788	0.569
Decision Favorability	3.341	0.057	3.229	3.454	3.423	0.059	3.309	3.538	3.295	0.062	3.173	3.418	3.334	0.053	3.230	3.438	0.947	0.861

Note: CI LL = 95% Confidence Interval Lower Level; CI UL = 95% Confidence Interval Upper Level.

methods such as opinion mining have demonstrated the capacity to capture public sentiment (Ceron & Negri, 2016; Dehler-Holland et al., 2022).

However, the results should also be interpreted in light of the institutional configurations tested in our experiment. In the HyDM condition, citizen-related information, such as local acceptance levels and demographic characteristics, was incorporated into the AI's assessment. Yet this input was included indirectly through data analysis rather than through visible public deliberation. In contrast, the HDM condition emphasized structured dialogue within a citizens' council as a salient participation mechanism. The higher input legitimacy attributed to HDM may therefore reflect differences in how participation was organised and made visible, rather than the presence of AI itself. Given that structured citizens' councils are not routinely implemented in planning processes, the HDM condition represents a participatorily enhanced version of the status quo. If HyDM were compared to conventional administrative procedures instead, the legitimacy gap might be smaller.

Regarding throughput and output legitimacy, HyDM is regarded as similarly legitimate as HDM, potentially because respondents assume that AI can solve certain problems better than humans, while human oversight remains in place to rectify possible errors. At the same time, this 'no difference' pattern may reflect a degree of ambivalence. Citizens may recognize the potential advantages of AI-supported processes, such as speed, data-processing capacity, and the promise of objectivity, yet simultaneously remain concerned about opacity, accountability gaps, or biased data. The insignificant difference between HyDM and HDM on the output dimension could indicate that citizens are willing to accept AI-supported arrangements when they appear capable of achieving substantive policy goals.

Our findings support some existing studies (e.g., Starke & Lünich, 2020) but contradict others. For instance, a representative population survey in Germany reveals limited general acceptance of AI in political decision-making (CAIS, 2023). One explanation for this discrepancy may be our use of a concrete policy scenario rather than a general question about AI in politics. While citizens may express general scepticism toward the abstract idea of AI in political decision-making, they may evaluate AI-supported arrangements more pragmatically when these are embedded in a specific and pressing policy context such as WPS. At the same time, our results do not indicate that respondents view HyDM as a comprehensive remedy for the often slow and conflict-prone democratic procedures that have complicated the transition to renewable energy. Rather, the hybrid arrangement appears to be seen as neither clearly superior nor clearly inferior.

These findings should also be understood against the backdrop of broader dissatisfaction with political processes. Traditional democratic decision-making has been characterized by declining political trust and increasing disenchantment (Newton et al., 2018; Trüdinger & Steckermeier, 2017), which has intensified calls for institutional innovation and more effective forms of engagement. In this context, digital technologies, data, and AI are frequently discussed as potential components of such innovation (Verhulst et al., 2019). However, our findings suggest that legitimacy judgments are shaped less by the mere presence of AI than by citizens' prior predispositions in this setting. The strong positive effects of trust in AI and trust in politics indicate that baseline attitudes play a substantial role in shaping evaluations. Moreover, HyDM appears to amplify the relevance of prior trust in AI: respondents with higher levels of AI trust are more likely to perceive the hybrid process as procedurally sound and acceptable, whereas input legitimacy and goal attainment remain largely unaffected by this moderation.

7.2. Security framing did not increase the legitimacy of HyDM

Notably, these results persist even when securitization is taken into account. Thus, we find no evidence that framing the energy crisis as a national-security issue increased or decreased the perceived legitimacy

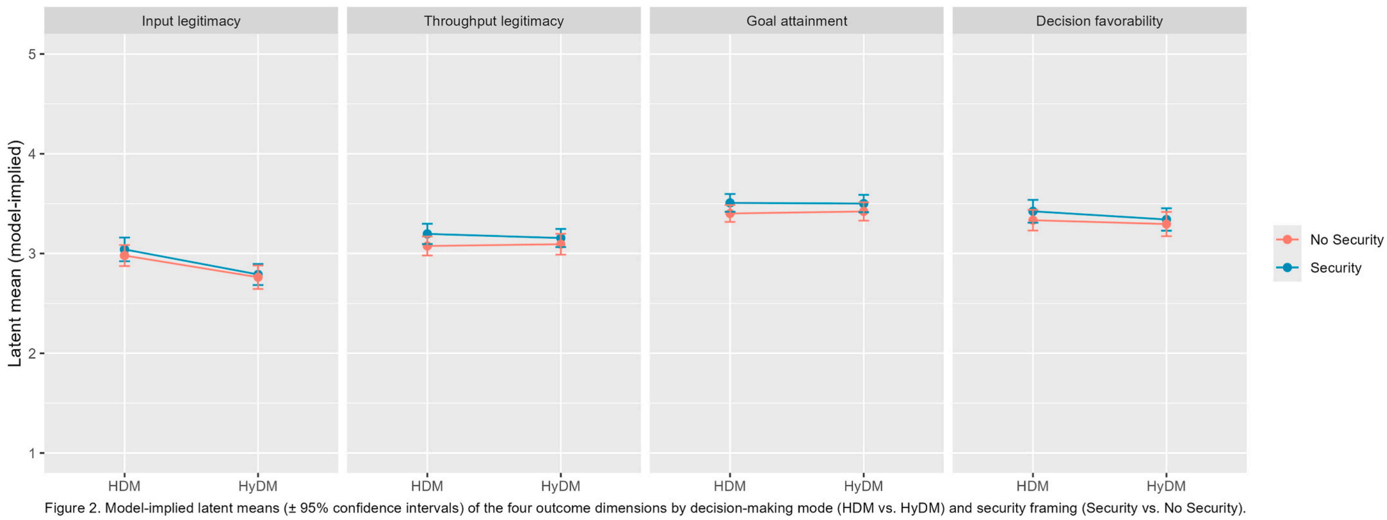

Fig. 2. Latent means.

of HyDM relative to HDM. This finding allows two interpretations, one regarding content and one regarding methodology. Content-related, the result indicates democratic resilience, suggesting a commitment to democratic principles. An interesting parallel can be drawn with the rally-around-the-flag effect. While this phenomenon typically relates to the consolidation of national identity during a crisis, our findings suggest that citizens display loyalty to established democratic processes instead, which may underscore their adherence to traditional democratic mechanisms, even in times of uncertainty. Methodologically, the null moderation may reflect limited treatment separation, given midpoint level security relevance even in the no-securitization conditions and the possibility that the manipulation check captures cue recognition rather than subjective threat appraisal or urgency.

However, the absence of a moderation effect by securitization could be partially attributed to Russia's full-scale invasion of Ukraine, the resulting energy crisis, and the existing public debate. As a result, the topic may have already been salient to many respondents, even in the absence of major developments during the duration of the study and the persistent presence of the conflict in public conversations for a considerable period. However, this salience could lead to underestimating potential effects, as the control group may need to adequately represent the baseline concerning an issue devoid of security matters.

For the use of AI technologies in policy-making, this pattern implies that securitizing issues is insufficient to build legitimacy. According to securitization theory, extraordinary measures become justifiable only when an audience accepts the speech act that elevates an issue to an existential threat. In our data, the securitization cue increased perceived security relevance, but this shift did not translate into higher legitimacy evaluations of HyDM relative to HDM. Accordingly, we interpret the result as no detectable legitimizing effect of securitization framing under the study's conditions.

7.3. Implications for policy-makers

The results of our study have implications for policy makers and public administrators. For public stakeholders, who recognize the potential of HyDM, these findings suggest that focusing on increasing public trust in the democratic potential of AI technologies is important for garnering support. Maintaining transparency and engaging in open dialogue with the public can enhance trust in politics and contribute to the perceived legitimacy of both HDM and HyDM. Such an approach may facilitate the successful integration of AI technologies across various policy domains, promoting more effective and responsive governance that aligns with societal values and expectations. However, HyDM may compromise perceived input legitimacy, thereby exacerbating the strain on already vulnerable democratic systems. Consequently, it may be advisable to utilize such technologies in a supplementary fashion, augmenting existing human processes rather than replacing them. By designing AI systems as supportive instruments, subject to human veto and ex-post scrutiny, governments may normalise their use without provoking concerns of technocratic exceptionalism. Policymakers, therefore, should not rely on security rhetoric to bypass deliberative demands. They must instead embed AI within transparent and accountable procedures that reaffirm democratic oversight. Without these safeguards, attempts to frame AI deployment as a national-security imperative risk reinforcing scepticism and entrenching public preference for conventional human decision-making.

7.4. Limitations and future research

Some limitations of our study suggest avenues for future research on the legitimacy of algorithmic decision-making. First, because we chose a simple and realistic HyDM scenario, namely AI-generated site proposals followed by human approval, the vignette necessarily simplifies the broader range of ways AI can be integrated into political decision-making. Future research should systematically examine how variations in AI configuration, such as the system's capabilities, data sources, transparency features, and level of decision-making autonomy, affect citizens' perceptions of democratic legitimacy.

Second, our experimental contrast between HDM and HyDM differs not only in the presence of AI but also in the structure of political input and the actors emphasized (a citizens' council vs. administrative decision-making based on AI-supported proposals). This design feature likely contributes to differences in perceived input legitimacy and limits the extent to which observed effects can be attributed to AI involvement alone. Moreover, the experimental design does not include an AI-only condition, which limits our ability to separately assess perceptions of AI assistance, human oversight, and their interaction. Future research should examine a broader set of institutional designs by varying both participatory architecture and the degree of algorithmic autonomy more systematically.

Third, while we distinguish two dimensions of output legitimacy (goal achievement and decision favourability), input and throughput legitimacy are treated more parsimoniously. Since both dimensions can be understood as multidimensional constructs (e.g., participation, voice, and representativeness for input legitimacy; fairness, transparency, and procedural quality for throughput legitimacy), our operationalization may not capture the full scope of legitimacy perceptions. Future studies

Table 3
Results 3 models.

Predictor	Dependent Variable	Model 1: B	Model 1: CI LL	Model 1: CI UL	Model 1: SE	Model 1: z	Model 1: p	Model 1: Beta	Model 2: B	Model 2: CI LL	Model 2: CI UL	Model 2: SE	Model 2: z	Model 2: p	Model 2: Beta	Model 3: B	Model 3: CI LL	Model 3: CI UL	Model 3: SE	Model 3: z	Model 3: p	Model 3: Beta
Type of Decision-Making[a]	Input Legitimacy	0.231	0.119	0.343	0.057	4.040	< 0.001	0.122	0.219	0.060	0.379	0.081	2.702	0.007	0.116	0.199	0.050	0.347	0.076	2.620	0.009	0.106
	Throughput Legitimacy	0.012	−0.086	0.110	0.050	0.239	0.811	0.007	−0.016	−0.155	0.124	0.071	−0.223	0.824	−0.010	−0.035	−0.151	0.081	0.059	−0.591	0.555	−0.021
	Goal Attainment	−0.008	−0.096	0.081	0.045	−0.171	0.864	−0.005	−0.026	−0.151	0.100	0.064	−0.401	0.688	−0.018	−0.030	−0.134	0.074	0.053	−0.567	0.570	−0.021
	Decision Favorability	0.060	−0.053	0.174	0.058	1.044	0.297	0.031	0.039	−0.122	0.200	0.082	0.474	0.636	0.020	0.037	−0.084	0.158	0.062	0.603	0.546	0.019
Securitization[b]	Input Legitimacy								0.035	−0.124	0.193	0.081	0.429	0.668	0.018	0.001	−0.148	0.150	0.076	0.017	0.987	0.001
	Throughput Legitimacy								0.064	−0.075	0.203	0.071	0.903	0.366	0.038	0.033	−0.084	0.149	0.059	0.552	0.581	0.020
	Goal Attainment								0.076	−0.049	0.201	0.064	1.191	0.234	0.054	0.060	−0.044	0.164	0.053	1.133	0.257	0.043
	Decision Favorability								0.046	−0.115	0.206	0.082	0.559	0.576	0.023	0.014	−0.107	0.135	0.062	0.224	0.823	0.007
TDM*Securitization	Input Legitimacy								0.022	−0.201	0.246	0.114	0.197	0.844	0.010	0.041	−0.168	0.251	0.107	0.386	0.700	0.019
	Throughput Legitimacy								0.056	−0.140	0.252	0.100	0.556	0.578	0.029	0.028	−0.136	0.192	0.084	0.335	0.737	0.015
	Goal Attainment								0.036	−0.141	0.212	0.090	0.396	0.692	0.022	−0.002	−0.148	0.144	0.075	−0.022	0.982	−0.001
	Decision Favorability								0.043	−0.184	0.269	0.116	0.371	0.711	0.019	−0.012	−0.182	0.159	0.087	−0.134	0.893	−0.005
Trust in Politics (TIP)	Input Legitimacy															0.241	0.173	0.309	0.035	6.935	<. 0.001	0.250
	Throughput Legitimacy															0.177	0.123	0.232	0.028	6.406	< 0.001	0.208
	Goal Attainment															0.084	0.035	0.133	0.025	3.333	0.001	0.116
	Decision Favorability															0.099	0.040	0.157	0.030	3.280	0.001	0.098
Trust in AI (TIAI)	Input Legitimacy															0.129	0.059	0.200	0.036	3.601	<. 0.001	0.126
	Throughput Legitimacy															0.165	0.109	0.221	0.029	5.797	< 0.001	0.182
	Goal Attainment															0.090	0.039	0.140	0.026	3.465	0.001	0.117
	Decision Favorability															0.185	0.124	0.245	0.031	5.992	< 0.001	0.172
Attitudes towards Wind Power	Input Legitimacy															0.175	0.072	0.279	0.053	3.321	0.001	0.132
	Throughput Legitimacy															0.478	0.393	0.564	0.043	10.996	< 0.001	0.407
	Goal Attainment															0.596	0.515	0.676	0.041	14.540	< 0.001	0.598
	Decision Favorability															0.878	0.779	0.976	0.050	17.412	< 0.001	0.632
Gender[c]	Input Legitimacy															−0.160	−0.268	−0.053	0.055	−2.931	0.003	−0.085
	Throughput Legitimacy															−0.028	−0.112	0.056	0.043	−0.648	0.517	−0.017

(*continued on next page*)

Table 3 (*continued*)

Predictor	Dependent Variable	Model 1: B	Model 1: CI LL	Model 1: CI UL	Model 1: SE	Model 1: z	Model 1: p	Model 1: Beta	Model 2: B	Model 2: CI LL	Model 2: CI UL	Model 2: SE	Model 2: z	Model 2: p	Model 2: Beta	Model 3: B	Model 3: CI LL	Model 3: CI UL	Model 3: SE	Model 3: z	Model 3: p	Model 3: Beta
	Goal Attainment															0.006	−0.069	0.081	0.038	0.154	0.877	0.004
	Decision Favorability															−0.049	−0.136	0.038	0.045	−1.101	0.271	−0.025
Age	Input Legitimacy															−0.001	−0.005	0.003	0.002	−0.411	0.681	−0.013
	Throughput Legitimacy															0.003	< 0.001	0.006	0.002	1.854	0.064	0.053
	Goal Attainment															0.002	−0.001	0.005	0.001	1.490	0.136	0.045
	Decision Favorability															−0.001	−0.004	0.003	0.002	−0.361	0.718	−0.009
Educational Attaintment	Input Legitimacy															0.009	−0.063	0.080	0.037	0.240	0.810	0.008
	Throughput Legitimacy															0.027	−0.029	0.083	0.029	0.955	0.340	0.027
	Goal Attainment															−0.043	−0.093	0.007	0.025	−1.688	0.092	−0.050
	Decision Favorability															0.028	−0.030	0.087	0.030	0.947	0.344	0.023
TDM*TIP	Input Legitimacy															0.029	−0.100	0.157	0.066	0.435	0.663	0.015
	Throughput Legitimacy															0.089	−0.013	0.191	0.052	1.705	0.088	0.052
	Goal Attainment															0.046	−0.047	0.138	0.047	0.968	0.333	0.032
	Decision Favorability															0.106	−0.004	0.216	0.056	1.881	0.060	0.052
Securitization*TIP	Input Legitimacy															0.114	−0.015	0.242	0.066	1.735	0.083	0.059
	Throughput Legitimacy															0.057	−0.045	0.159	0.052	1.104	0.270	0.034
	Goal Attainment															−0.005	−0.098	0.087	0.047	−0.114	0.909	−0.004
	Decision Favorability															< 0.001	−0.110	0.110	0.056	−0.005	0.996	< 0.001
TDM*TIAI	Input Legitimacy															−0.111	−0.248	0.026	0.070	−1.586	0.113	−0.054
	Throughput Legitimacy															−0.119	−0.228	−0.010	0.055	−2.145	0.032	−0.066
	Goal Attainment															−0.039	−0.137	0.06	0.050	−0.772	0.440	−0.025
	Decision Favorability															−0.139	−0.256	−0.022	0.060	−2.327	0.020	−0.065
Securitization*TIAI	Input Legitimacy															−0.112	−0.248	0.025	0.070	−1.603	0.109	−0.054
	Throughput Legitimacy															< 0.001	−0.108	0.109	0.055	0.004	0.997	< 0.001
	Goal Attainment															0.051	−0.047	0.149	0.050	1.023	0.306	0.033
	Decision Favorability															0.043	−0.073	0.160	0.060	0.730	0.465	0.020

Note: CI LL = 95% Confidence Interval Lower Level; CI UL = 95% Confidence Interval Upper Level
[a] Hybrid Decision-making = 0 and Human Decision-making = 1.
[b] Security Frame Not Present = 0 and Security Frame Present = 1.
[c] Male = 0 and Female = 1

should therefore use multidimensional legitimacy measures to assess whether specific subdimensions are particularly sensitive to AI involvement and crisis framing. Accordingly, effects on input and throughput legitimacy should be read as overall differences in perceived inclusiveness and procedural quality, not as evidence about specific subdimensions.

A fourth limitation concerns the strength of our securitization manipulation. While respondents clearly noticed the security-related framing in the manipulation check, this item primarily captures recognition of a national-security reference and therefore does not guarantee that the stimulus conveyed a meaningful sense of threat or urgency. Taken together, the midpoint-level threat ratings in the no-securitization conditions and the small estimated effects raise the possibility that our null interaction findings reflect a relatively attenuated manipulation, rather than the absence of any underlying securitization effect. Future studies should therefore pre-test the emotional impact of security framings, employ stronger stimuli, and measure perceived urgency and threat more directly.

Since our data were collected before the widespread diffusion of generative AI and NLP for private users, recent advances mainly improve the technical implementation of HyDM (e.g., scalability and user interfaces), but they may also alter perceptions of transparency, accountability, and contestability in such systems. These developments do not necessarily change the core governance questions we examine—such as decision authority, human oversight, and accountability—but they may change how these issues are perceived by citizens. Future research should evaluate NLP-based implementations in comparable institutional settings to determine whether they affect citizens' legitimacy perceptions.

Finally, assessing the impact of public engagement and communication strategies is warranted. Communication approaches and public involvement in the development and deployment of democratic AI systems may help identify practices that foster legitimacy. Despite relatively low public approval of AI's use for democratic decision-making, HyDM is mostly perceived as neither more nor less legitimate than traditional human forms of decision-making. What implementation modes, then, may tip the scale in favour of one or the other? Longitudinal studies could track changes in public perceptions of legitimacy over time, as AI technologies evolve and become increasingly prevalent in decision-making processes. This approach could provide insights into attitudinal shifts in response to technological developments and national security threats. As the securitization framing of the issue did not have an effect in our study, questions remain concerning the effectiveness of alternative framing approaches and communication strategies. By pursuing these research directions, scholars can gain a deeper understanding of the factors that contribute to the perceived legitimacy of algorithmic decision-making and inform the development and implementation of democratic AI systems that align with societal values.

8. Conclusion

This study examined the public's perceptions of the legitimacy of using AI-assisted HyDM to identify potential locations for WPS. Additionally, the study examined the moderating effect of securitization (i.e., framing the energy supply issue as a matter of national security) on these perceptions. Drawing upon the literature on AI in policy decisions, automated decision-making, and securitization theory, we found only minor differences in the perceived legitimacy of HyDM compared to HDM for WPS siting. The securitization of the issue did not moderate these relationships in our experiment. Our findings indicate that attitudes towards wind power, trust in politics, and trust in AI were the primary drivers of legitimacy perceptions. These results suggest that policymakers and public administrators should approach the application of HyDM in political decision-making with caution and provide evidence that speaks to the democratic legitimacy of proposed designs. Additionally, academic research needs to elucidate the social dynamics surrounding HyDM and their consequences for the social acceptance of AI technologies. Ultimately, one should not prematurely dismiss traditional democratic processes of HDM in favour of HyDM, but rather compare their respective merits prudently.

CRediT authorship contribution statement

Marco Lünich: Writing – review & editing, Writing – original draft, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jule Roth:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Christopher Starke:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Conceptualization.

Availability of data, code, and material

The data and code for data analysis can be accessed via the project's Open Science Foundation repository (https://osf.io/2wbd3/overview?view_only=c79b844fec61404cb4c233e7ee9ecfff).

Declaration of generative AI in scientific writing

During the preparation of this work the authors used ChatGPT in order to produce and adjust R and Markdown code for the statistical analysis and the reproducible manuscript. We also used ChatGPT to revise and shorten parts of our written draft of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Conflicts of interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techsoc.2026.103327.

Data availability

Data and code for analysis are provided via OSF: https://osf.io/2wbd3/overview?view_only=c79b844fec61404cb4c233e7ee9ecfff.

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