Public Response to Government Use of AI Technology in Emergencies: Evidence from Covid-19

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Abstract

In the effort to contain the COVID-19 outbreak and mitigate its consequences, many hopes were placed on the use of AI-technology. Indeed, AI-based algorithms have informed decision-making in many aspects of the crisis, including diagnosis, infection tracking, outbreak forecasting, and allocation of essential resources and services. How do citizens view the incorporation of AI technology in making major public policy decisions? Using original survey data from the U.S. and Israel, I show that citizens trust humans significantly more than algorithms in making high-stake decisions related the pandemic. However, experimental evidence indicates that this clear preference does not translate uniformly into lower support for policies that rely on algorithmic assessment. Rather, views on the use of algorithms differ substantially depending on the decision context in which it is deployed. The analysis indicates that while deployment of AI in public policy may be acceptable in some cases, it could trigger substantial opposition in other, theoretically-predictable contexts.

[*]I declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. I received no financial support for this research.

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Introduction

Recent years have seen a significant rise in the use of algorithmic decision systems (ADSs) to assist or replace human decision-making in a wide variety of public policy contexts. Decisions in policing, criminal sentencing, child protection, and social welfare assistance are increasingly being informed by AI-based algorithms - computer software that autonomously makes decisions without using explicit human instruction, relying on data-driven inference instead. Considering that these decisions affect high-stakes social interactions, they carry profound ethical and political implications. Despite the major social ramifications of such decisions, government agencies frequently procure and implement algorithmic systems behind closed doors, without the knowledge or consent of those most affected by these systems: the public. A key question is how the public will perceive the growing prevalence of ADSs in public policy, especially as people become more aware of them.

Public knowledge and approval of using ADSs in public policy are crucial to establishing their legitimacy in policymaking, particularly when citizens are obliged to accept unfavorable decisions. The importance of addressing public opinion becomes clear in light of previous attempts to deploy ADSs, without first gauging the public's views, which have met significant opposition that ultimately resulted in their termination. A recent example occurred in the UK, when students organized large protests against a new algorithm that was used to predict and assign grades as a replacement for their final exams that were canceled due to the COVID-19 pandemic. These protests eventually caused the government to reverse its decision to use this algorithm for determining college placement (Simonite, 2020).

The question of public approval has become even more pertinent in light of the momentum that these systems have gained during the COVID-19 pandemic. ADSs are playing a pivotal role in almost every aspect of the crisis response, including diagnosing virus cases, providing early detection by predicting and tracking infections, monitoring social distancing, and allocating essential resources and services (e.g., Chiusi et al., 2020).

From the early stages of the crisis, high hopes have been placed on the ability of ADSs to help contain the outbreak and mitigate its numerous consequences through automation. Proponents contend that by providing data-driven analysis on a scale, scope, and time frame that humans cannot perform as effectively, algorithms may help deploy government resources and deliver public services more efficiently and objectively (e.g. Lepri et al., 2018; Miller, 2018). However, research casts doubt on this idea by highlighting a range of ethical concerns about the use of ADSs, such as racial bias and discrimination against marginalized groups; perpetuation of societal inequities; a lack of transparency and accountability; and privacy violations (e.g. Barocas and Selbst, 2016; Pasquale, 2015). Recently, scholars and journalists have begun warning against the temporary use of these tools, specifically surveillance technologies, to manage and monitor the outbreak and spread of the pandemic. The concern is that the pandemic may normalize the use of these new technologies and might lead to the permanency of what should have been short-term emergency measures (Nay, 2020).

Much of this research rests on an implicit assumption that, without knowledge of algorithms' potential harms, people view ADSs as an attractive solution, especially during times of crisis.[1] Yet, despite the heated debate surrounding the development and implementation of these systems, we have a limited understanding of what the public thinks about the use of ADSs in public policy, particularly in the context of COVID-19 responses. To date, only a few studies have explored public attitudes toward the use of AI in the public sector, and the few studies that have been conducted provide inconclusive evidence (Kennedy, Waggoner, and Ward, 2018; Zhang and Dafoe, 2019).

To address this gap, this article examines public attitudes toward the use of ADSs in the

[1] For example, as O'neil (2016) stated, "algorithms are opinions embedded in code. It's really different from what most people think of algorithms. They think algorithms are objective and true and scientific.". Similarly, Eubanks (2018) wrote that: "one of the great benefits of these tools for governments is it allows them to portray the decisions they are making as neutral and objective...".

context of the pandemic. Using original survey data from the U.S. and Israel, I demonstrate that citizens, by a wide margin, prefer that humans, rather than algorithms, make high-stakes decisions related to managing the ongoing pandemic and that this strong preference crosses demographic, ideological, and party lines. Yet, the fact that people largely prefer human decision-making does not necessarily indicate that they would oppose policy proposals involving algorithmic decision-making. People may be indifferent to, or not even notice, the decision-maker when evaluating proposed policies on the pandemic, especially considering people's tendency during times of crisis to accept and adopt technologies that would not be accepted, and may even be opposed, during ordinary times (Noah Harari, 2020). The question that arises is whether and how the use of algorithms affects people's willingness to support policies proposed to contain the pandemic.

Studies suggest that decisions are more supported when made in a way viewed as neutral, rule-based, and free of bias (Levi, Sacks, and Tyler, 2009). Assuming that algorithms make decisions based on rules applied consistently and neutrally over time and across different parties and situations, several studies indicate that such technology has the potential to increase fairness in decision-making (Lee et al., 2019; Sunstein, 2019). However, I argue that this notion of fairness pertains only to a particular type of decision rather than to all decisions made in the public sector and that the extent to which people are sensitive to ADSs depends in part on the type of decision under consideration. Specifically, I distinguish between two common decisions in the public sector depending on the objective of the decision.

To evaluate the effects of ADSs on support for policies, I designed a survey experiment that manipulates the decision-maker (an algorithms vs. a human) and the decision type (deciding which individuals receive tests for COVID-19 vs. which regions to lock down in response to COVID-19). The analysis provides support to my contention that the effect of ADSs on support depends on the type of decision at hand. The results show that ADSs have no effect on the evaluation of which individuals should be prioritized for COVID-19 tests, which involves a specific procedure and repetitive decision-making. By contrast, the same algorithmic system decreases the perceived fairness of, and support for, a proposal to impose regional lockdowns on specific areas rather than on an entire population. This policy involves conflict between health and economic interests and violations of fundamental rights, such as freedom of movement. The observed effects are both statistically significant and substantively meaningful. Having a predictive algorithm decide which areas to lock down and which to leave open significantly decreases support from a 57% majority to 45%—an effect even larger than the partisan differences in policy support between Democrats and Republicans.

To assess the replicability of these U.S. findings in a different national context, I conducted a similar survey experiment in Israel, a country that has had three full lockdowns since the beginning of the outbreak. Israel was one of the first countries to implement advanced technology, on the basis of emergency regulations, to monitor outbreaks. Despite this and the broad public support for policy proposals that impose selective instead of national lockdowns, I found that ADSs significantly reduce support and perceived fairness of a regional lockdown policy.

Taken together, these findings provide new insights into the debate on public acceptance of the deployment of advanced technologies in times of emergency and specifically in response to the ongoing COVID-19, which has so far focused on surveillance and contact tracing technologies (Zhang et al., 2020; Ziller and Helbling, 2020). By expanding the scope to other policy decision areas in which ADSs are proposed to be deployed, the study shows that people's attitudes depend on policy context. The study, therefore, also contributes to the evolving research on algorithmic fairness, which emphasizes the role of ADSs' technical features and design such as accuracy and transparency (see, e.g., Chouldechova and Roth, 2020; Fine Licht and Fine Licht, 2020). By showing how the fairness of the same algorithmic system, which assesses risks by predicting virus outbreaks, can be perceived differently in different decision areas, this study indicates that the perceived fairness of ADSs is also influenced by the decision context in which they are implemented.

Research Design

To assess whether and how the use of algorithms affects people's willingness to support policies proposed to contain the pandemic, I designed an experiment embedded in a nationally representative survey of 1,480 American adults.[2] Respondents were asked to evaluate one of two policy proposals for managing various aspects of the pandemic.

First, to assess the effect of using ADSs on support, I manipulated the identity of the decision-maker. All respondents evaluated the same policy proposal with one important difference, in the control the decision-makers were public health officials, while in the treatment it was a predictive algorithm. Second, to test whether the effect of the decision-maker varies with the type of decision being made, I manipulated the policy that respondents were asked to evaluate. As noted, I distinguish between two types of public-sector decisions: procedural decisions applied to individuals, such as whom to stop in speed driving, and political decisions applied to collectives, such as which neighborhoods to patrol.

The policies were therefore chosen according to this distinguishing factor. One policy is to impose regional lockdowns instead of a national lockdown. This policy implies that a decision-maker decides which geographic areas to place under a lockdown and which to leave open. This decision directly affects collectives and deals with conflicting interests such as public health vs. economic health and fundamental values including freedom of movement. The political nature of this decision is particularly striking, in light of the evidence for the expanding segregation that intensifies connections between geography, social groups, and political interest (Enos, 2017). A second policy proposal is about deciding who will receive tests first. This is more of a technical decision that are routinely applied to individuals.

[2] Information about the survey, IRB approval, and summary statistics reported in the Appendix

As summarized in Table 1, in total the experiment includes two manipulations with two conditions each. The balance tests reported in Appendix A2, indicates that the treatment and control groups are balanced on key socio-demographic covariates.

Experimental Conditions

		Decision Type	
		Political	Procedural
Decision Maker	A Human	1. Lockdown Public health officials	2.Testing Public health officials
	An Algorithm	3. Lockdown A predictive algorithm	4.Testing A predictive algorithm

The main dependent variable measures support for the proposed policy. Respondents were asked to indicate to what degree they support or oppose the policy proposal. I also measure two additional outcomes that capture the main considerations taken into account when evaluating the proposed policy: the perceived fairness and effectiveness of the policy. After evaluating the proposal, respondents were presented with the second type of decision-maker and were asked to indicate which of the two options they trust more to make the right decision.

Results

Preferences for ADSs

I begin by analyzing respondents' preferences for using algorithmic decision-making (DM) versus human DM in the two policy contexts. As noted, respondents were asked directly whether a predictive algorithm or public health officials should decide, in a context that was randomly assigned. Figure 1 presents the distribution of preferences for each policy.

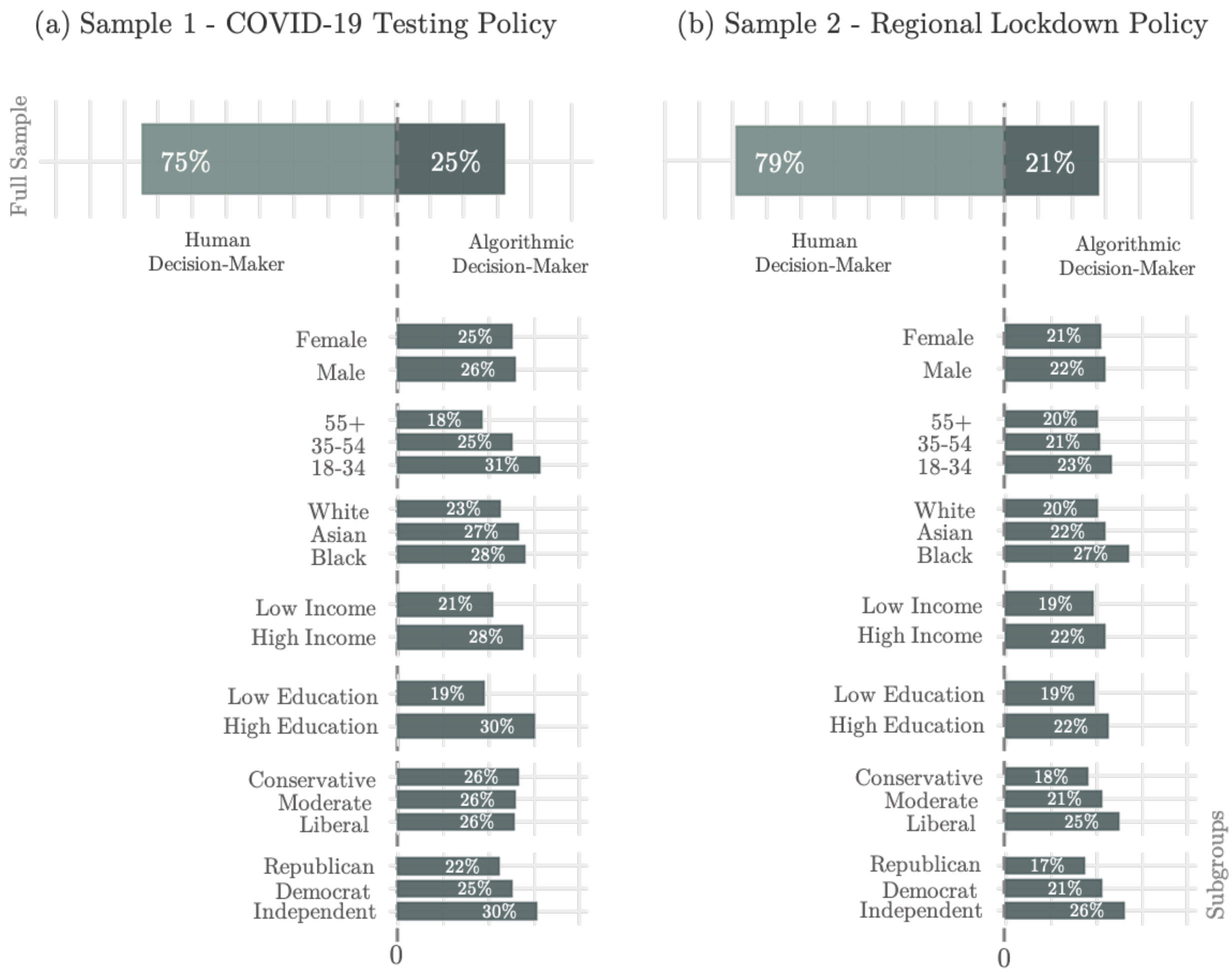
The figure shows that an overall majority of respondents trust humans more than algorithms to make the right decisions in managing the pandemic. Such a clear preference for human DM was found in both policy contexts, as 79 percent of respondents who evaluated the regional lockdown policy (and 72 percent of respondents who evaluated the proposal to prioritize testing) indicated that decisions should be made by public health officials rather than by a predictive algorithm [3]

The general preference for human DM may also mask divisions along demographic, ideological, or party lines. Indeed, previous studies have shown that men, younger people, higher educated people, and higher earners are more likely to support the development of AI (e.g., Zhang and Dafoe, 2019; Smith, 2018). Despite a few differences, Figure 1 shows that the share of respondents who favor ADSs is low across all subgroups, as it does not exceed 35 percent for either policy.

Nevertheless, the fact that people preferred that humans rather than algorithms make decisions related to the management of the pandemic does not necessarily indicate that they would oppose or react negatively to policy proposals involving ADSs. Therefore, it remains unclear whether and how the use of algorithms affects people's willingness to support policies proposed to contain the pandemic. One possibility is that in line with the stated preferences, ADSs provoke a negative reaction and decreases support for COVID-19 policies. An alternative possibility is that, despite their clear preference for human DM, people may not express significant opposition to ADSs in times of crisis (Noah Harari, 2020). Drawing on evidence from research on human-computer interactions (HCI), which has recently shown that people are more averse to algorithmic decisions in tasks that require 'human' skills (e.g., subjective judgment and emotional capability) than those that require 'mechanical' skills (e.g., processing quantitative data for objective measures) (e.g., Logg, 2017; Lee, 2018), I propose a third possibility: the effect of ADSs depends on the decision context in which they are deployed.

[3] As Table SI-6 shows, the coefficient of algorithmic condition is statistically insignificant, indicating that the decision-maker treatment presented in the previous question had no priming effect on preferences

Figure (1) Preference for ADSs - Full Sample and Subgroups

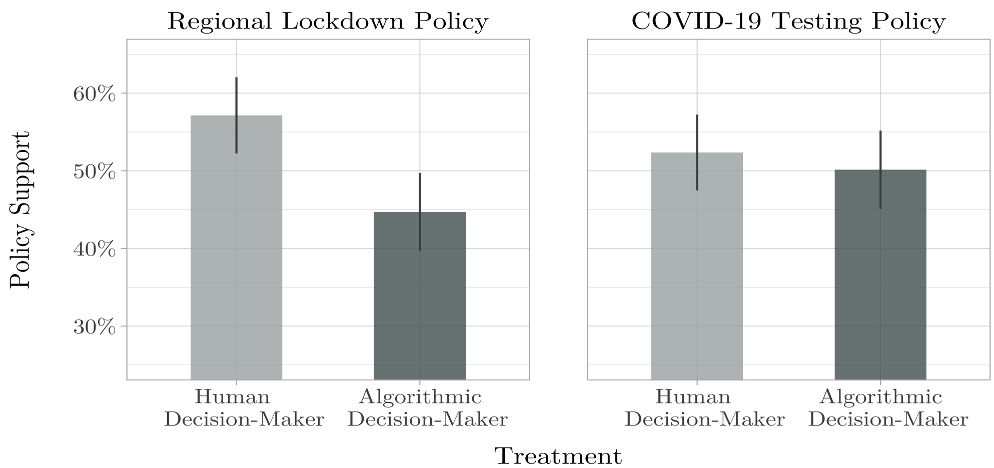


Notes: Upper panels show the percentage of preference for ADM over HDM in testing policy (N=782) and lockdown policy (N=768). Lower panels display the share of respondents in each subgroup who favor ADM..

The Effect of ADSs on Policy Support

The three expectations will be examined, using a survey experiment that assesses whether and how using ADSs affects support, and whether such an effect depends upon the decision type. I begin by analyzing the impact of algorithmic treatment on support for the policies. The outcome of interest is a binary variable that takes the value 1 if the respondent strongly or somewhat supports the policy and '0' otherwise. Figure 2 displays the average support for each policy as a function of the decision-maker condition.

Figure (2) Average Policy Support By Decision-maker and Decision-Type



Notes: Error bars indicate 95% CIs.

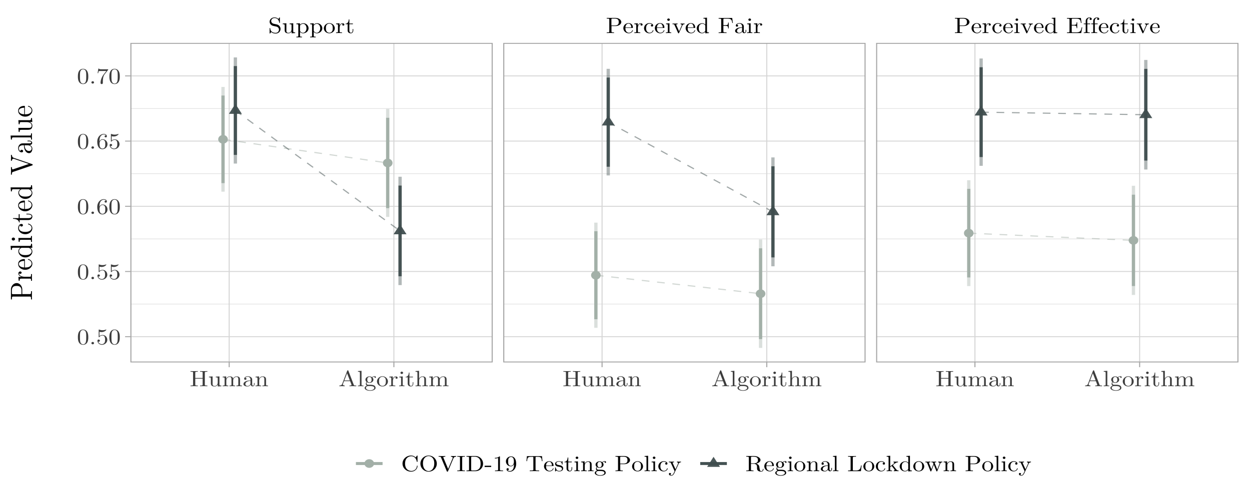
The results show that respondents who were presented with algorithmic DM were 13 percentage point less likely to support the regional lockdown policy than those who were presented with a human DM. The effect was not only statistically significant but also politically meaningful, as it decreased support from a majority of 57 percent to less than 45 percent. To get a better sense of this effect, figure SI-1 demonstrates that this effect is larger than the difference in support between Democratic and Republican respondents, making it even more striking given the polarization in the public debate over the appropriate policy responses to the pandemic.

Regarding the policy of prioritizing testing, there is no evidence of any difference in the effects of algorithmic DM and human DM on the average support. As shown in Appendix A6, all results are consistent when using OLS regression with controls and alternative measures of the outcome. While people strongly prefer human over algorithmic decisions when asked directly about the alternatives, they are indifferent to algorithmic decisions in procedural types of policy.

Interaction Between Decision-Maker and Decision-Type

To test the possibility that the policy context moderates the effect of ADSs, I examine the interaction effect of the decision-maker and the policy-type treatments on the policy evaluation in terms of support, fairness, and effectiveness. Figure 3 shows the results from OLS models regressing the three outcomes on dummies for each treatment and the interaction between them. In line with my expectation, there is a positive interaction between the decision-maker and the decision type for the effects on support ($p<0.1$) and perceived fairness ($p<0.05$) but not for the effect on the perceived effectiveness of the policy.

Figure (3) Conditional Effects of Decision-Maker and Decision-Type on 3 Outcomes



Notes: Results of OLS regressions in which the three outcomes (binary) are regressed on the decision-type and the decision-maker, and their interaction. Models do not include controls. Thick bars represent 90% CIs; thin bars represent 95% CIs.

Table SI-13 shows that the proposal to prioritize individuals receiving COVID-19 testing eliminate the negative effect of ADS on perceived fairness, changing it from a 10 percentage point decrease in the case of the lockdown policy decision to a 2-point increase. In contrast, when assessing the policy's effectiveness, the table shows that in all decision types, it makes no difference whether an algorithm or a human makes the decision. Notably, the difference in treatment effects on the perceived fairness versus effectiveness indicates that the respondents' answers did not reflect a general feeling toward ADSs, but rather that respondents thought separately about these various dimensions when evaluating the policy. Therefore, the results may be interpreted as indicating that people are open to the use of algorithms in public-sector decision-making but that such openness depends on the policy.

The Israeli Case

So far, the findings suggest that when policy decisions about lockdowns at the regional level are made by an algorithm, they receive less support and are perceived as less fair than those made by humans. However, the question arises whether these findings are unique to the context of the U.S., which gives states the freedom to decide upon their own lockdown policies. The uniqueness of the U.S. case is especially striking given the deepening partisan polarization of recent years, which has also been reflected in the public debate over the severity of COVID-19 (Druckman et al., 2020).

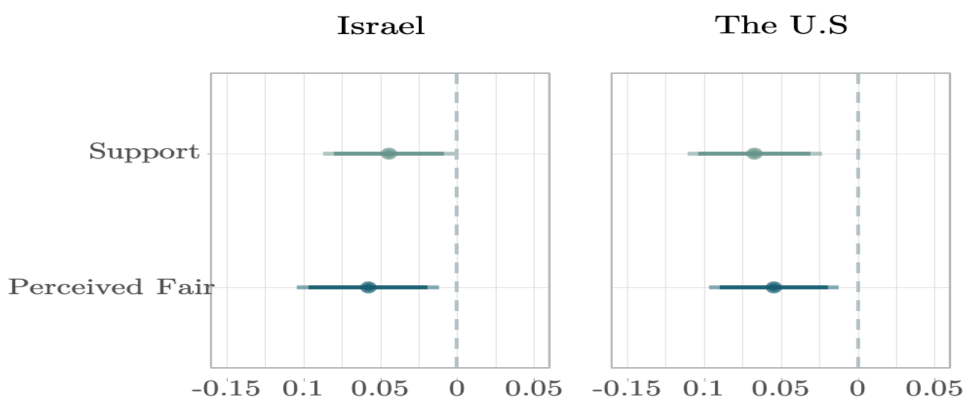
To assess whether the results are also valid for other settings, I conducted a similar survey in Israel (N = 800) which included a replication of the regional lockdown experiment.[4] For several reasons, Israel provides an interesting test for the hypothesis that people are susceptible to a negative view of the use of algorithms in lockdown decision-making. First, the use of advanced technologies in policy-making is not new to the Israeli public. Indeed, Israel was one of the first countries to use emergency regulations to implement advanced location-

[4] The survey was fielded in January 2021, when tests for COVID-19 were no longer considered a limited resource. Therefore, the second scenario of prioritizing testing was not relevant.

tracking technology to monitor and eradicate COVID-19 outbreaks (Lomas, 2020; Singer, 2020). Second, after long periods of full lockdown, it seems that the majority of Israelis strongly support the idea of regional lockdowns. In the public discourse about the second lockdown, policy-makers were criticized on the grounds that the decision to impose a national lockdown was motivated by political rather than professional considerations (Hermann and Anabi, October 2020).[5] Specifically, it was claimed that the prime minister succumbed to pressures from his ultra-Orthodox constituents, who live in areas that have the highest infection rates.

Despite these facts, the findings from the analysis of the Israeli sample are similar to those obtained from the U.S. sample. As Figure SI-3 in Appendix B2 shows, when asked directly about their preferences, a large majority of Israeli respondents (about 69%) indicated that public health officials should decide which geographic areas to lock down.

Figure (4) Effects of ADSs - Israel vs The U.S.



Notes: Results of OLS models without controls in which each outcome are coded to range from 0 to 1. Thick bars represent 90% CIs; thin bars represent 95% CIs.

I estimate the average treatment effects of the decision-maker on public support and the perceived fairness of the regional lockdown policy. As expected, when looking at the baseline levels of support, regardless of the treatment received, I find that the proposal of a regional

[5] A survey by the Israel Democracy Institute found that over half (55%) of Israelis believe that the nationwide lockdown was solely or mainly politically motivated.

lockdown is highly popular. Measured on a scale ranging from 0 to 1, the mean level of support was 0.72, compared with 0.59 in the U.S. study.

Despite the high level of support, Figure 4 indicates that using an algorithm to decide which areas to lock down has a significant negative effect on both the support for, and the perceived fairness of, the policy. The results remain substantively similar when including controls and using alternative measures (See Appendix B3).[6] More specifically, tables SI-24 and SI-25 shows no significant interaction between the decision-maker and being either Orthodox or living in a red-city, two groups that experienced high infection rates and therefore might have had a greater interest in this policy. The lack of interaction implies that people evaluate the procedure itself regardless of the expected outcome or the degree of interest they have in the outcome. To conclude, the Israeli case suggests that the negative effect of the use of ADSs on evaluating a regional lockdown policy is valid even in circumstances that made the proposal of regional lockdowns particularly attractive.

Conclusion and Discussion

The extensive implementation of ADSs in the public sector has triggered an intense debate among policymakers, practitioners, and scholars concerning the conditions under which ADSs are acceptable. This debate has been reflected in a series of public and private initiatives to define the ethical principles that should guide the development and regulation of AI technology for advancing social good. Examples are Microsoft's expert group FATE and the ADSs Task Force of New-York City. Most of these initiatives do not consider the attitudes of the public—the people who will have to live with, act on, and accept the authority of ADSs. Yet, even if engineers and ethicists were to agree on how ADSs should be operated,

[6] Probably due to high levels of baseline support, when the outcome was coded as a binary that took the value 1 if the respondent strongly or somewhat supported the policy, the result was non-significant. However, estimating the likelihood of strong support for the proposed policy, Table SI-23 shows a significant negative effect of 10 percentage point in the Israeli sample and 8 percentage point in the U.S. sample.

it would have limited value if citizens strongly rejected these views.

The findings in this short paper highlight the need for a study of public perceptions, especially on the ethics discussion, which relies on relatively strong assumptions about what people think about algorithms and how they evaluate their use in the public sector. Contrary to prevalent assumptions in this debate which suggest that in the absence of knowledge, people naively view ADSs as a more attractive solution than human decision-making (e.g., Eubanks, 2018; O'neil, 2016), this study shows that most people are skeptical about using AI algorithms to manage the COVID-19 crisis.[7]

However, the analysis also indicates that these strong preferences for human decision-making do not uniformly translate into less support for policies that rely on ADSs. The same algorithm affects public perception differently depending on the decision context in which it is deployed. Overall, the analysis lends support to the argument that, due to their impersonal nature, algorithms do not provoke significant opposition when used in procedural decisions. Nevertheless, this same lack of agency makes algorithm deployment significantly undesirable in politically charged decisions about collectives, which are decisions in which the expectation is to treat people in a way that is not detached from their socio-cultural background. In such decisions, the understanding of fairness in terms of non-discrimination, which is also common among computer scientists, is less appropriate.

Yet, one must be careful not to overinterpret these findings because the experiment examined only two decision scenarios. While focusing on COVID-19 policy decisions offers a difficult test for this argument given people's tendency during emergencies to accept—as temporary policy measures—advanced technologies that they would not at other times,

[7]For example, as O'neil (2016) stated, "algorithms are opinions embedded in code. It's really different from what most people think of algorithms. They think algorithms are objective and true and scientific. That's a marketing trick [...] A lot can go wrong when we put blind faith in big data". Such an assumption is also implied in Eubanks (2018)'s words, who wrotes that: "one of the great benefits of these tools for governments is it allows them to portray the decisions they are making as neutral and objective, as opposed to moral decisions".

supporting the theory requires a more systematic examination that includes a variety of decision-making scenarios from a broader range of policy domains. Therefore, this study serves as a starting point for a broader research agenda that will guide understanding of how AI can be used in the public domain. Specifically, this study has methodological implications for how AI perceptions might be addressed. It demonstrates the promise of using experiments to assess the potential reactions of citizens to the growing deployment of AI in public policy in a way that might not be possible through direct survey questions.

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SUPPLEMENTARY INFORMATION

A Study 1: US Survey

The survey was fielded by the survey company Lucid between between April 9 and April 14, 2020 – slightly more than one month after the widespread recognition of COVID-19. I used quota sampling to ensure that the distributions of socio-demographic characteristics such as age, gender, ethnicity, race, and education in the sample were matched to those in the U.S. population as measured by the census. Summary statistics of the sample are reported in Table SI-4.

A.1 Survey Questionnaire

This section presents the exact wording of the policy scenarios included in the survey. As mentioned, respondents were asked to evaluate one of two policy proposals for managing various aspects of the COVID-19 pandemic. To minimize the potential concern of social desirability, respondents were not informed about the study focuses on using ADSs. Instead, they were asked about their views on different aspects of the ongoing pandemic.

Regional Lockdown Policy As part of the effort to slow down the spread of the coronavirus pandemic, many countries are implementing full lockdowns on the entire population. However, such a policy has heavy economic costs. To minimize these costs, some propose that *[T1: senior public health officials; T2: a predictive computer algorithm]* will decide which areas need to have a lockdown and which areas do not, based on their assessment of the risk of a coronavirus outbreak in the area.

- **Support**: Some people find this procedure acceptable, while others find it unacceptable. To what degree do you support or oppose this process of having *[T1: senior public health officials decide; T2: a predictive computer algorithm decides]* on the specific geographic areas to lockdown?

- **Fairness**: To what degree do you think the proposed policy of targeting specific geographic areas to lockdowns is fair?

- **Effectiveness**: To what degree do you think the policy of targeting specific geographic areas to lockdowns is effective?

- **Preference**: In the scenario you just saw, *[T1: senior public health officials decide; T2: a predictive computer algorithm decides]* which areas need to have a lockdown and which areas do not. This decision, however, can also be made by *[T1: senior public health officials; T2: a predictive computer algorithm]*. Which of the following decision-makers do you trust to make the right decisions?

COVID-19 Testing Policy The number of people who ask for coronavirus testing exceeds the amount of testing that can be performed. To manage this shortage, *[T1: senior public health officials decide ;T2: a predictive computer algorithm decides]* which individuals will receive the test first, prioritizing those who live in geographic areas that are assessed to be more at risk of an infection outbreak.

- **Support**: Some people find this procedure acceptable, while others find it unacceptable. To what degree do you support or oppose the process of having *[T1: senior public health officials decide; T2: a predictive computer algorithm decides]* prioritize which individuals receive a test for coronavirus?
- **Fairness**: To what degree do you think the proposed policy of prioritizing which individuals receive a test for coronavirus based on geographic location is fair?
- **Effectiveness**: To what degree do you think the proposed policy of prioritizing which individuals receive a test for coronavirus based on geographic location is effective?
- **Preference**: In the scenario you just saw, *[T1: senior public health officials decide; T2: a predictive computer algorithm decides]* which individuals will receive coronavirus test first. This decision, however, can also be made by *[T1: senior public health officials; T2: a predictive computer algorithm]*. Which of the following decision-makers do you trust to make the right decisions?

A.2 Summary Statistics and Balance Checks

The below tables show that balance on the following covariates: gender, age, education, race and party affiliation is maintained among the four conditions: lockdown policy with algorithmic DM; lockdown policy with human DM; testing policy with algorithmic DM and testing policy with human DM. Each table presents the mean value for the covariate under each condition as well as the p-value from a chi-squared test. The first column of each table considers the full sample.

Table (SI-1) By Gender

	Full Sample	ADS Lockdown	ADS Testing	HDS Lockdown	HDS Testing
Female	52.77	50.8	54.09	50.51	53.6
Male	47.23	49.2	45.91	49.49	46.4
N	1607	376	379	392	403

Chi-squared test of independence: X-squared = 1.6; df = 3; p-value = 0.66

Table (SI-2) By Age

	Full Sample	ADS Lockdown	ADS Testing	HDS Lockdown	HDS Testing
18-34	32.79	34.31	36.41	25.26	34.24
35-54	39.39	39.63	39.58	42.35	36.97
55+	27.82	26.06	24.01	32.4	28.78
N	1607	376	379	392	403

Chi-squared test of independence: X-squared = 15.78; df = 6; p-value = 0.01

Table (SI-3) By Race

	Full Sample	ADS Lockdown	ADS Testing	HDS Lockdown	HDS Testing
Asian	6.1	5.59	6.86	6.38	5.71
Black	13.88	14.63	12.4	13.52	14.89
Hispanic	17.98	15.96	20.05	16.84	17.87
White	60.42	62.23	58.84	61.48	60.3
Other	1.62	1.6	1.85	1.79	1.24
N	1607	376	379	392	403

Chi-squared test of independence: X-squared = 4.71; df = 12; p-value = 0.97

A.3 Preferences Analysis - Additional Results

A.3.1 General Preference for Algorithmic Decision Maker - Interaction with Treatment Conditions

The table below reports the results of ordinary least squares regression models studying the effect of the two experimental treatments on the probability of preferring algorithmic over human decision-making.

Table (SI-4) By Education

	Full Sample	ADS Lockdown	ADS Testing	HDS Lockdown	HDS Testing
Less than high school	6.72	6.91	6.86	5.36	6.7
High school diploma	34.66	35.37	33.51	32.91	36.23
Some college	19.73	21.81	18.73	21.17	17.12
Associate's degree	10.39	7.71	10.03	12.24	11.41
Bachelor's degree	16.8	17.29	19	16.58	15.88
Graduate degree	11.7	10.9	11.87	11.73	12.66
N	1607	376	379	392	403

Chi-squared test of independence: X-squared = 10.71; df = 15; p-value = 0.77

Table (SI-5) By Party ID

	Full Sample	ADS Lockdown	ADS Testing	HDS Lockdown	HDS Testing
Republican	32.85	34.78	29.95	35.92	30.79
Independent	28.32	27.17	31.28	27.91	26.97
Democrat	38.83	38.04	38.77	36.18	42.24
N	1522	368	374	387	393

Chi-squared test of independence: X-squared = 6.54; df = 6; p-value = 0.37

A.3.2 Preference for ADSs - Subgroup Analysis

Table (SI-6) ADS Preferences and Treatment Conditions

	Dependent variable:	
	Prefer ADS over HDS	
	(1)	(2)
Decision Type (Lockdown)	-0.042^{*}	-0.045^{*}
	(0.021)	(0.022)
Decision Maker (ADS)		-0.015
		(0.022)
Constant	0.254^{**}	0.300^{**}
	(0.015)	(0.034)
Demographics	No	Yes
Observations	1,550	1,516
R^2	0.002	0.025

Notes: This table reports the results of ordinary least squares regression models studying the effect of the two experimental treatments on the probability to prefer algorithm over human decision-making. The models also control for the decision-maker condition presented in the previous question. The base categories of the key independent variables are the testing policy (decision type) and human decision-maker (decision-maker identity). Thus, the last row of the table reports the baseline probabilities of support for the policy proposal to prioritize individuals to receive tests for COVID-19 by public health officials. Column 1 reports estimates from a minimal specification, while column 2 reports estimates from a regression models adjust for respondents' socio-demographic characteristics: gender, age, race, education, income and party affiliation. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

Table (SI-7) The Correlates of Preference for Using Algorithmic Decision Making, by Policy

	Dependent variable:			
	Prefer Algorithms over Human DM			
	Lockdown Policy		Testing Policy	
	(1)	(2)	(3)	(4)
Female	0.003	0.001	0.005	0.008
	(0.030)	(0.030)	(0.032)	(0.032)
Age 55+	−0.032	−0.036	-0.090^{*}	-0.103^{*}
	(0.041)	(0.041)	(0.043)	(0.043)
Age 35-54	−0.034	−0.038	−0.057	−0.066
	(0.037)	(0.037)	(0.038)	(0.038)
Asian	−0.004	−0.006	0.021	0.026
	(0.065)	(0.064)	(0.066)	(0.066)
Black	0.041	0.046	0.068	0.070
	(0.048)	(0.046)	(0.052)	(0.050)
Hispanic	−0.007	−0.009	0.097^{*}	0.108^{*}
	(0.045)	(0.044)	(0.044)	(0.043)
Other	0.002	0.015	0.122	0.139
	(0.115)	(0.115)	(0.139)	(0.140)
Low Education	−0.035	−0.031	-0.114^{**}	-0.115^{**}
	(0.033)	(0.033)	(0.034)	(0.034)
Low Income	−0.023	−0.022	−0.047	−0.051
	(0.037)	(0.037)	(0.039)	(0.039)
Moderate		−0.031		0.023
		(0.039)		(0.040)
Liberal		−0.058		0.061
		(0.045)		(0.046)
PID (Democrat)	0.032		0.003	
	(0.037)		(0.039)	
PID (Independent)	0.082^{*}		0.060	
	(0.039)		(0.042)	
Constant	0.229^{**}	0.297^{**}	0.313^{**}	0.306^{**}
	(0.045)	(0.051)	(0.048)	(0.050)
Demographics	No	Yes	No	Yes
Observations	751	751	765	764
R^2	0.013	0.009	0.041	0.040

Notes: The table reports coefficients from OLS models. The dependent variable is an indicator variable that takes the value one if an individual prefers ADM over HDM. Standard errors reported in parentheses. All models control for the decision maker treatment. Baseline categories are as follows: male, age 18-36, high education, non white, high income, Republican, Covid-19 Testing policy. *p < .1; **p < .05; ***p < .01

A.4 Experimental Evidence

A.4.1 Different Measures of Outcome Variables

The tables below report summary statistics of the outcome variables – support, fairness and effectiveness – in two different measures.

Table (SI-8) Summary Statistics of Outcomes (Dummy Variable)

Sample	Treatment	Mean	N	SD	SE
COVID-19 Testing Policy	Support	0.51	782	0.50	0.02
	Fairness	0.21	782	0.41	0.01
	Effectiveness	0.22	782	0.42	0.01
Regional Lockdown Policy	Support	0.51	768	0.50	0.02
	Fairness	0.35	768	0.48	0.02
	Effectiveness	0.38	768	0.48	0.02

Table (SI-9) Summary Statistics of Outcomes (point-scale)

Sample	Outcome	Mean	N	SD	SE
COVID-19 Testing Policy	Support	3.38	782	1.16	0.04
	Fairness	4.15	782	1.67	0.06
	Effectiveness	4.28	782	1.64	0.06
Regional Lockdown Policy	Support	3.37	768	1.24	0.04
	Fairness	4.62	768	1.79	0.06
	Effectiveness	4.76	768	1.77	0.06

A.4.2 Average Treatment Effects

Table (SI-10) Support for Policies - Average Treatment Effects

	Algorithmic Decision-Maker Mean	Human Decision-Maker Mean	TE (95% CI)	p-value (two-tailed)
Regional Lockdown Policy	0.442	0.575	-0.133 (-0.204, -0.061)	0.000
COVID-19 Testing Policy	0.504	0.524	-0.020 (-0.092, 0.051)	0.572

Notes: This table reports the group means and differences by decision maker and policy context. n = 734 Lockdown policy; n = 746 testing policy.

A.4.3 Additional Results - OLS regressions

This section provides results for estimated effects of the use of ADSs on alternative measures of support. In Model 1, the outcome is a binary variable that takes the value of 1 if the respondent indicated, "strongly supports" or "somewhat supports" the proposed policy. In Model 2 the explained variable gets the value 1 if the respondent answered, "strongly supports" the proposed policy, and the value 0 if otherwise. In the third model, the outcome is measured on a five-point scale, with higher values indicating greater levels of support.

Table (SI-11) The Effect of Decision-Maker on Support or Strongly Support For Regional Lockdown Policy

	Dependent variable:			
	Support		Strongly Support	
	(1)	(2)	(3)	(4)
Decision-maker - Algorithm decide	-0.125^{**}	-0.130^{**}	-0.083^{**}	-0.089^{**}
	(0.036)	(0.036)	(0.029)	(0.029)
Constant	0.571^{**}	0.732^{**}	0.247^{**}	0.357^{**}
	(0.025)	(0.093)	(0.020)	(0.076)
Demographics	No	Yes	No	Yes
Observations	768	751	768	751
R^2	0.016	0.054	0.010	0.050

Notes: This table reports the results of ordinary least squares regression models studying the effect of algorithmic decision-maker on the likelihood to support the proposal of regional lockdown policy. The dependent variable is encoded in two different ways. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

Table (SI-12) The Effect of Decision-Maker on Support or Strongly Support for the COVID-19 Testing Policy

	Dependent variable:			
	Support		Strongly Support	
	(1)	(2)	(3)	(4)
Decision-maker - Algorithm decide	−0.022	−0.016	−0.015	−0.004
	(0.036)	(0.036)	(0.027)	(0.027)
Constant	0.524**	0.695**	0.179**	0.297**
	(0.025)	(0.094)	(0.019)	(0.070)
Demographics	No	Yes	No	Yes
Observations	782	765	782	765
R^2	0.0005	0.059	0.0004	0.063

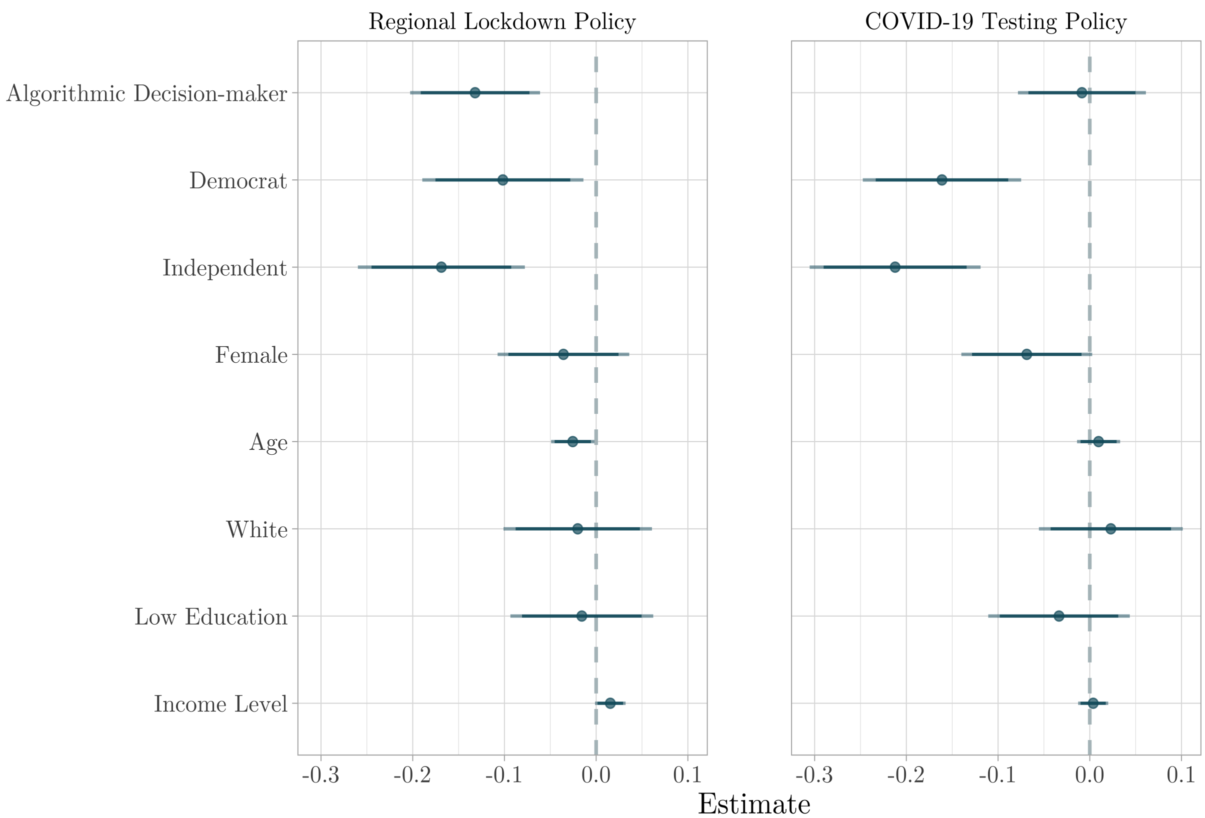
Notes: This table reports the results of ordinary least squares regression models studying the effect of algorithmic decision-maker on the likelihood to support and strongly support the proposal of regional lockdown policy. The dependent variable is encoded in two different ways. *p < .1; **p < .05; ***p < .01

Table (SI-13) The Interaction Between Decision-Maker and Decision-Type

	Dependent variable:					
	Support		Perceived Fair		Perceived Effective	
	(1)	(2)	(3)	(4)	(5)	(6)
Decision-Maker (Algorithm Decides)	−0.125**	−0.124**	−0.105**	−0.103**	−0.010	0.005
	(0.036)	(0.036)	(0.032)	(0.032)	(0.033)	(0.032)
Decision Type (Testing Policy)	−0.048	−0.039	−0.207**	−0.210**	−0.162**	−0.155**
	(0.035)	(0.035)	(0.031)	(0.031)	(0.032)	(0.032)
Algorithm Decides x Testing Policy	0.102*	0.108*	0.123**	0.126**	0.019	0.007
	(0.051)	(0.051)	(0.045)	(0.045)	(0.046)	(0.046)
Constant	0.571**	0.731**	0.406**	0.508**	0.380**	0.459**
	(0.025)	(0.068)	(0.022)	(0.061)	(0.023)	(0.062)
Demographics	No	Yes	No	Yes	No	Yes
Observations	1,550	1,516	1,550	1,516	1,550	1,516
R^2	0.008	0.046	0.034	0.067	0.028	0.074

Notes: This table reports the results of OLS regression models studying the interaction between the decision-maker and the decision-type on perceived fairness and effectiveness. The base categories of the key independent variables are human DM and the regional lockdown policy. Thus, the table's last row reports the baseline probabilities of support for the proposal of regional lockdown policy decided by public health officials. Models 2 and 4 adjust for respondents' socio-demographic characteristics: gender, age, race, education, income and party affiliation. *p < .1; **p < .05; ***p < .01

Figure (SI-1) Effects of Algorithmic Decision-Making on Support for COVID-19 policies



Notes:This Figure reports the estimates results of ordinary least squares regressions studying the effect of algorithmic decision-maker on the likelihood to support the proposal of regional lockdown policy (left panel) and COVID-19 testing policy (right panel). Thick bars represent 90% confidence intervals; thin bars represent 95% confidence intervals. *p < .1; **p < .05; ***p < .01

Table (SI-14) Interaction - Decision-Maker and Decision-Type

	Dependent variable:											
	Support		Strongly Support		Somewhat Fair		Very Fair		Somewhat Effective		Very Effective	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Decision-Maker (Algorithm Decides)	-0.125^{**}	-0.124^{**}	-0.083^{**}	-0.086^{**}	-0.078^{*}	-0.076^{*}	-0.057^{*}	-0.054^{*}	0.0005	0.016	0.001	0.007
	(0.036)	(0.036)	(0.028)	(0.028)	(0.036)	(0.036)	(0.026)	(0.026)	(0.036)	(0.036)	(0.027)	(0.027)
Decision Type (Testing Policy)	−0.048	−0.039	-0.069^{*}	-0.075^{**}	-0.151^{**}	-0.150^{**}	-0.135^{**}	-0.137^{**}	-0.127^{**}	-0.108^{**}	-0.115^{**}	-0.118^{**}
	(0.035)	(0.035)	(0.028)	(0.027)	(0.035)	(0.035)	(0.026)	(0.026)	(0.035)	(0.035)	(0.026)	(0.027)
Algorithm Decides x Testing Policy	0.102^{*}	0.108^{*}	0.067	0.082^{*}	0.055	0.053	0.076^{*}	0.078^{*}	−0.028	−0.044	0.024	0.025
	(0.051)	(0.051)	(0.040)	(0.039)	(0.050)	(0.050)	(0.037)	(0.037)	(0.050)	(0.050)	(0.038)	(0.038)
Constant	0.571^{**}	0.731^{**}	0.247^{**}	0.364^{**}	0.546^{**}	0.684^{**}	0.235^{**}	0.299^{**}	0.574^{**}	0.690^{**}	0.222^{**}	0.322^{**}
	(0.025)	(0.068)	(0.020)	(0.053)	(0.025)	(0.068)	(0.018)	(0.050)	(0.025)	(0.068)	(0.019)	(0.051)
Demographics	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,550	1,516	1,550	1,516	1,550	1,516	1,550	1,516	1,550	1,516	1,550	1,516
R^2	0.008	0.046	0.008	0.055	0.019	0.054	0.022	0.057	0.020	0.065	0.020	0.053

Notes: This table reports the results of ordinary least squares regression models studying the interaction between the decision-maker treatment and the decision type treatment on perceived fairness and effectiveness.The base categories of the key independent variables are human decision maker (decision maker identity) and the regional lockdown policy (decision's type). Thus, the table's last row reports the baseline probabilities of support for the proposal of regional lockdown policy decided by public health officials. Models 2, 4 and 6 adjust for respondents' socio-demographic characteristics: gender, age, race, education, income and party affiliation. *p < .1; **p < .05; ***p < .01

B Study 2: Israel Survey

In this section I provide information and report additional results from the second survey experiment that was conducted in Israel.

B.1 Summary Statistics and Balance Checks

The below tables demonstrate that balance on the following covariates: gender, age, education, orthodox and political ideology is maintained among the two conditions: lockdown policy with algorithmic DM; lockdown policy with human DM. Each table shows the mean value for the covariate under each condition as well as the p-value from a chi-squared test. The first column of each table considers the full sample.

Table (SI-15) By Gender

	Full Sample	ADS Lockdown	HDS Lockdown
18-34	22.342	23.989	20.699
35-45	35.128	30.728	39.516
55+	42.530	45.283	39.785

Chi-squared test of independence: X-squared = 0.71; df = 1; p-value = 0.4

Table (SI-16) By Age

	Full Sample	ADS Lockdown	HDS Lockdown
18-34	166	89	77
35-45	261	114	147
55+	316	168	148
N	743	371	372

Chi-squared test of independence: X-squared = 0.63; df = 4; p-value = 0.18

Table (SI-17) By Education

	Full Sample	ADS Lockdown	HDS Lockdown
High Education	61.78	61.46	62.1
Low Education	38.22	38.54	37.9
N	743	371	372

Chi-squared test of independence: X-squared = 0.03; df = 2; p-value = 0.98

Table (SI-18) By Political Ideology

	Full Sample	ADS Lockdown	HDS Lockdown
Center	30.21	32.08	28.49
Left	11.1	9.7	12.63
Right	58.69	58.22	58.87
N	748	371	372

Chi-squared test of independence: X-squared = 2.24; df = 4; p-value = 0.69

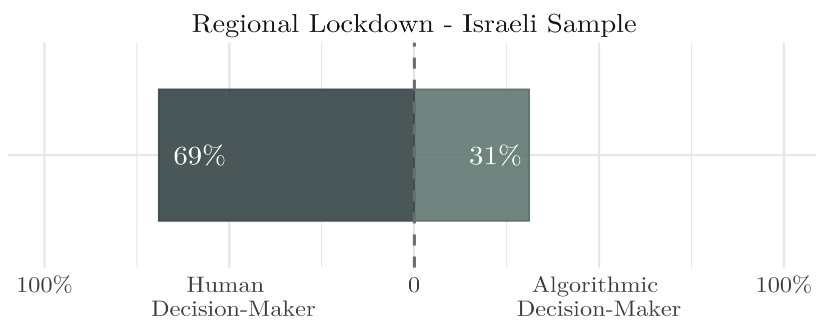
Table (SI-19) By Being Orthodox

	Full Sample	ADS Lockdown	HDS Lockdown
0	683	340	340
1	65	31	32

Chi-squared test of independence: X-squared = 0.04; df = 2; p-value = 0.98

B.2 Preference for Algorithmic DM - Full Sample

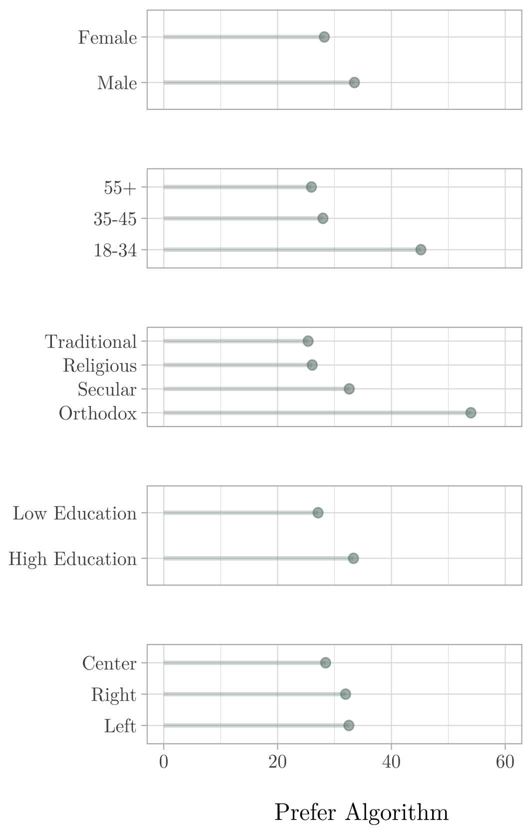
Figure (SI-2) Distribution of Preferences in Israel



Notes: This figure shows the percentage of preferences algorithmic over human decision making in deciding which region to lock down (N= 800).

B.3 Preference for Algorithmic DM - Subgroup Analysis

Figure (SI-3) Favor Algorithmic DM over Human DM across social and demographic characteristics



Notes: This figure reports the percentage of respondents in each subgroup who favors using algorithms over human decision makers.

Table (SI-20) The Correlates of Preference for Using Algorithmic Decision Making

	Dependent variable:		
	Prefer ADS over HDS		
	(1)	(2)	(3)
Ideology (Right-wing)		-0.021	
		(0.035)	
Trust in Gov			-0.089^{*}
			(0.045)
Low Education	-0.089^{*}	-0.090^{*}	-0.086^{*}
	(0.035)	(0.035)	(0.035)
Orthodox	0.200^{**}	0.203^{**}	0.188^{**}
	(0.063)	(0.063)	(0.063)
Age 35-45	-0.150^{**}	-0.153^{**}	-0.144^{**}
	(0.047)	(0.047)	(0.047)
Age 55+	-0.158^{**}	-0.163^{**}	-0.157^{**}
	(0.046)	(0.046)	(0.045)
Female	-0.034	-0.036	-0.035
	(0.034)	(0.034)	(0.034)
Constant	0.463^{**}	0.479^{**}	0.476^{**}
	(0.044)	(0.051)	(0.044)
Observations	743	743	743
R^2	0.050	0.050	0.055

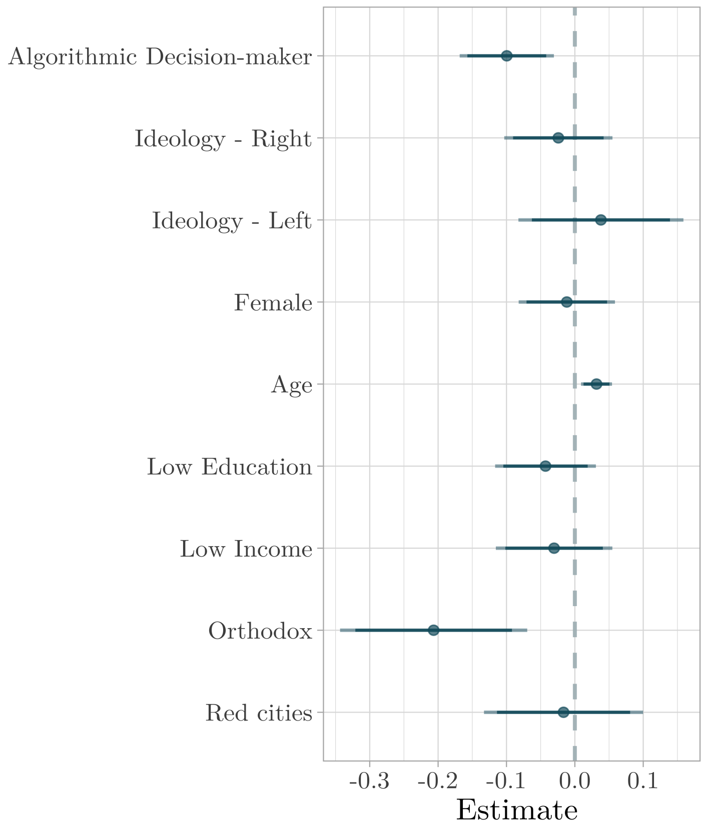
Notes: The table reports coefficients from linear probability models. The dependent variable is an indicator variable that takes the value one if an individual prefers ADM over HDM. Standard errors reported in parentheses. All models control for the decision maker treatment. Baseline categories are as follows: male, age 18-36, high education, non white, high income, Republican, Covid-19 Testing policy. *p < .1; **p < .05; ***p < .01

B.4 Experimental Analysis

Table (SI-21) Different Measures of Outcome Variables

Sample	Treatment	Mean	N	SD	SE
Regional Lockdown Policy	Support (binary)	0.70	743	0.45	0.01
	Support (5 categories)	0.72	743	0.30	0.01
	Strongly Support (binary)	0.38	743	0.48	0.01
	Perceived Fair (binary)	0.50	743	0.50	0.01
	Perceived Fair (7 categories)	4.99	743	1.94	0.07
	Perceived Very Fair (binary)	0.32	743	0.47	0.01

Figure (SI-4) Effects of Algorithmic Decision-Making on Support for Regional Lockdown Policy



Notes: This figure shows the results of OLS regressions in which each outcome is regressed on a binary treatment indicator that has the value of 1 for respondents who were exposed to algorithmic DM and 0 for those who presented with human DM. Thick bars represent 90% confidence intervals; thin bars represent 95% confidence intervals. The regression model adjusts for respondents' socio-demographic characteristics: gender, age, education, ideology, being an Orthodox, and living in a red city (which includes cities marked as areas with a high infection rate: Elad, Beitar Ilit, Modi'in Ilit, Rekhasim, Jerusalem, Kafr Qassem, Nazareth, Tiberias, Umm al-Fahm, Daliyat al-Karmel, Maale Iron, and Rechasim).

Table (SI-22) The Effect of Decision-Maker on Support Lockdown Policy

	Dependent variable:											
	Israel Sample						The U.S. Sample					
	Attitudes		Support		Strongly Support		Attitudes		Support		Strongly Support	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Decision-maker - Algorithm decide	-0.044^{*}	-0.047^{*}	-0.044	-0.041	-0.099^{**}	-0.105^{**}	-0.067^{**}	-0.074^{**}	-0.125^{**}	-0.131^{**}	-0.083^{**}	-0.089^{**}
	(0.022)	(0.021)	(0.034)	(0.033)	(0.036)	(0.035)	(0.022)	(0.022)	(0.036)	(0.036)	(0.029)	(0.029)
Constant	0.742^{**}	0.736^{**}	0.723^{**}	0.645^{**}	0.438^{**}	0.498^{**}	0.624^{**}	0.699^{**}	0.571^{**}	0.711^{**}	0.247^{**}	0.349^{**}
	(0.015)	(0.037)	(0.024)	(0.058)	(0.025)	(0.063)	(0.016)	(0.040)	(0.025)	(0.064)	(0.020)	(0.052)
Demographics	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	743	743	743	743	743	743	768	755	768	755	768	755
R^2	0.006	0.100	0.002	0.079	0.010	0.052	0.012	0.040	0.016	0.044	0.010	0.043

Notes: his table reports the results of ordinary least squares regression models studying the effect of the algorithmic decision-maker treatment on support for regional lockdown policy. The outcome variables are measured in thee different ways. Models 2, 4, 6 and 8 adjust for respondents' socio-demographic characteristics: gender, age, education, political ideology and being orthodox. *p < .1; **p < .05; ***p < .01

Table (SI-23) The Effect of Decision-Maker on Support Lockdown Policy

	Dependent variable:							
	Fairness		Fair		Fairness		Fair	
	Israel Sample				The U.S. Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Decision-maker - Algorithm decides	-0.058^{*}	-0.059^{**}	-0.063	-0.062	-0.055^{*}	-0.053^{*}	-0.105^{**}	-0.100^{**}
	(0.024)	(0.022)	(0.037)	(0.036)	(0.021)	(0.022)	(0.034)	(0.035)
Constant	0.691^{**}	0.735^{**}	0.540^{**}	0.588^{**}	0.627^{**}	0.597^{**}	0.406^{**}	0.408^{**}
	(0.017)	(0.040)	(0.026)	(0.063)	(0.015)	(0.038)	(0.024)	(0.061)
Demographics	No	Yes	No	Yes	No	Yes	No	Yes
Observations	743	743	743	743	768	755	768	755
R^2	0.008	0.134	0.004	0.085	0.008	0.032	0.012	0.035

Notes: This table reports the results of ordinary least squares regression models studying the effect of the algorithmic decision-maker treatment on the perceived fairness for regional lockdown policy. The outcome variables two measured in thee different ways. Models 2, 4, 6 and 8 adjust for respondents' socio-demographic characteristics: gender, age, education, political ideology and being orthodox. *p < .1; **p < .05; ***p < .01

Table (SI-24) Interaction Effects on Decision-Maker on Support for the Lockdown Policy

	Dependent variable:			
	Strongly Support			
	(1)	(2)	(3)	(4)
Decision-maker - Algorithm decide	-0.103^{**}	-0.110^{**}	-0.096^{*}	-0.104^{**}
	(0.037)	(0.037)	(0.038)	(0.037)
Orthodox	-0.308^{**}	-0.263^{**}		-0.245^{**}
	(0.089)	(0.093)		(0.070)
Red City		−0.023	−0.096	−0.014
		(0.059)	(0.084)	(0.086)
Algorithm X Orthodox	0.043	0.040		
	(0.126)	(0.126)		
Algorithm X Red City			−0.005	−0.017
			(0.115)	(0.113)
Constant	0.465^{**}	0.514^{**}	0.448^{**}	0.513^{**}
	(0.026)	(0.058)	(0.027)	(0.058)
Demographics	No	Yes	No	Yes
Observations	743	743	743	743
R^2	0.037	0.054	0.014	0.053

Notes: This table reports the results of OLS regression models studying the interaction between the decision-maker treatment and being Orthodox (in models 1 and 2) and living in a red city (models 3 and 4), on support for the lockdown policy. Models 2, and 4 adjust for respondents' socio-demographic characteristics: gender, age, education, and political ideology. *p < .1; **p < .05; ***p < .01

Table (SI-25) Interaction Effects on the Perceived Fairness of Lockdown Policy

	Dependent variable:			
	Perceived Fairness			
	(1)	(2)	(3)	(4)
Decision-maker - Algorithm decide	-0.115^{**}	-0.124^{**}	-0.107^{**}	-0.116^{**}
	(0.035)	(0.035)	(0.036)	(0.036)
Orthodox	-0.346^{**}	-0.306^{**}		-0.231^{**}
	(0.085)	(0.089)		(0.067)
Red City		-0.007	-0.121	-0.036
		(0.057)	(0.081)	(0.082)
Algorithm X Orthodox	0.149	0.150		
	(0.122)	(0.121)		
Algorithm X Red City			0.064	0.050
			(0.110)	(0.109)
Constant	0.409^{**}	0.473^{**}	0.391^{**}	0.472^{**}
	(0.025)	(0.055)	(0.026)	(0.055)
Demographics	No	Yes	No	Yes
Observations	743	743	743	743
R^2	0.040	0.066	0.015	0.064

Notes: This table reports the results of OLS regression models studying the interaction between the decision-maker treatment and being Orthodox (in models 1 and 2) and living in a red city (models 3 and 4), on the perceived fairness of the lockdown policy. Models 2, and 4 adjust for respondents' socio-demographic characteristics: gender, age, education, and political ideology. *p < .1; **p < .05; ***p < .01

B.5 Research Ethics

The study relied on two surveys. One was conducted through the online platform Lucid and the second one was implemented by Israel's largest online panel company, IPanel. Both surveys were reviewed and approved by IRB before the study was initiated (protocol numbers: 0001277-1 and 0002199-1). They were complied using the current standards for research transparency and ethics, including the American Political Science Association's "Principles and Guidance for Human Subjects Research" as approved by the APSA Council in April, 2020.

Informed consent was obtained from each participant at the beginning of the surveys. Specifically, in both surveys, respondents were informed that (1) the survey was voluntary, (2) they could exit it at any time without penalty, and (3) they were free to decline to answer any particular question.

Respondents were reimbursed by the survey firms with standard compensation. Moreover, the survey companies did not provide any identifying data, such as names or email addresses, so that the data used in the analysis and provided for the replication would be anonymous. Finally, the policy proposals that respondents were asked to evaluate were based on real initiatives, in order to incorporate AI technologies. This means that the experiment did not include false information.