THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Mandate or Motivate?

A Conjoint Experiment on Agency and Stringency in COVID-19 Booster Vaccination Policies

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Abstract

In May 2023, the World Health Organisation (WHO) declared the end of the COVID-19 public health emergency. However, its impact on society reveals that medical solutions, such as vaccines, alone are insufficient for effective pandemic response strategies, behavioural insights are equally decisive. While prior research has explored the impact of vaccine attributes on uptake, little is known about how policy design shapes public acceptance. Drawing on a large-scale conjoint experiment with 42,417 participants across all G7 countries, this study explores how different levels of policy stringency and agency impact the individual willingness to choose COVID-19 booster vaccination policies. The results show that preferences for agency-enhancing interventions depend on the availability of alternatives. Individuals accepted moderate reductions in opportunity freedom when paired with enhanced process support, such as clinics offering scheduling assistance, but only when the alternatives did not substantially reduce their opportunity freedom. When more controlling options were available, participants preferred full autonomy. Regarding stringency, soft interventions like social norms campaigns increased the likelihood of policy choice (+5.6 percentage points), while stringent measures led to diverging outcomes, with people choosing mandates (+0.5 – 1.4 percentage points) and avoiding fines (-8.7 – -9.6 percentage points). The general attitude towards stringent measures was moderated by trust in the vaccine, stressing the importance of trust-building in public health. This study offers the first systematic categorisation of policy interventions based on agency levels and provides insights for designing more publicly accepted vaccination strategies as the next pandemic is not a question of *if*, but *when*.

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Table of Abbreviations

AMCE: Average Marginal Component Effect

BCW: Behavioural Change Wheel

COM-B: Capability, Opportunity and Motivation Behaviour

COVID-19: Coronavirus Disease

GP: General Practitioner

G7: Group of 7

GPMB: Global Preparedness Monitoring Board

HBM: Health Belief Model

LIMCs: Low- and Middle-Income Countries

NPI: Non-Pharmaceutical Intervention

OECD: Organisation for Economic Cooperation and Development

OLS: Ordinary Least Squares

OSF: Open Science Framework

OxCGRT: Oxford COVID-19 Government Response Index

UK: United Kingdom

USA: United States of America

WEIRD: Western, Educated, Rich, Industrialised, Democratic

W1 & W2: Wave 1 and Wave 2

*: Figures built with PowerPoint

Overview of Tables and Figures

The associated code can be found on GitHub

1. Introduction

"The next pandemic will not wait until things calm down. […]. *This is not a theoretical risk; it is an epidemiological certainty" (World Health Organisation, 2025)*

With these words, Dr. Tedros Adhanom, the current Director-General of the WHO, opened his speech during the intergovernmental negotiation panel on the WHO Pandemic Agreement Board in 2025. In his remarks, he stressed the global urge to enhance pandemic preparedness. The COVID-19 pandemic, which started in January 2020 with the outbreak of the SARS-CoV-2 virus in China, exposed critical vulnerabilities in global health systems and led to over 7 million reported deaths worldwide (World Health Organisation, 2022). While both the economy and health system are currently recovering from the pandemic impact, the threat of future pandemics remains. According to the Global Preparedness Monitoring Board (GPMB), there are constant smaller outbreaks of high-consequence diseases being recorded every year, leading to an estimated outbreak probability of a pandemic comparable in scale to COVID-19 of 2% (Global Preparedness Monitoring Board, 2024). As climate change accelerates and human activity continues to disrupt natural habitats, the risk of emerging infectious diseases is thus constantly rising (Srivastava et al., 2024).
While scientific advances, such as the development of mRNA vaccines, have transformed our technical ability to respond to new pandemics, the existence of vaccines alone does not guarantee broad immunisation: successful pandemic response also depends on public acceptance of vaccination policies. During the COVID-19 pandemic, vaccine scepticism and hesitancy have increased in many regions, fuelled by misinformation and declining trust in institutions (Siani & Tranter, 2022). Thus, a growing body of literature suggests a significant impact of behavioural factors on shaping public acceptance of vaccinations (Michie, 2022).
While many studies have explored the impact of vaccine characteristics on vaccine uptake, such as efficacy (Koenig et al., 2024), or exogenous factors such as pandemic severity (Alsan et al., 2023; Hartmann et al., 2024), fewer have systematically analysed how policy design factors affect vaccine uptake. Recent empirical work indicates that varying levels of policy stringency, the policy intrusiveness, and individual agency, the ability to deliberately choose, could impact vaccine uptake, nevertheless, these factors have not yet been systematically analysed together in an experimental study (Dixson & Samaddar, 2021; Koenig et al., 2024).

To address this gap, I aim to systematically investigate how varying levels of agency and policy stringency drive public acceptance of vaccine policies via a conjoint analysis. Conjoint studies have been widely used to evaluate public preferences for vaccines during COVID-19, for example, by analysing how vaccines should be prioritised (Duch et al., 2021) or how sensitive people are to the framing of side effects (Stöckli et al., 2022), thereby making this analysis suitable. Drawing on a publicly available data set, derived from a large-scale survey conducted in 2022 with 42,417 participants across all Group-of-Seven (G7) countries, I analysed how different levels of agency provision regarding vaccine scheduling and reminders, and stringency, represented by campaigns, mandates and fines, impact the public acceptance of COVID-19 vaccine policies. This thesis not only contributes to previous research on vaccination policy effectiveness but also amends a growing stream of literature on agency in public policy (Banerjee, Grüne-Yanoff, et al., 2024). In particular, this is the first paper aiming to categorise interventions based on their degree of provided agency, thereby contributing to future research on agency-enhancing interventions in the field.

By shifting the focus towards policy stringency and agency, I aim to inform more effective and ethically desirable vaccination strategies for the future.

2. Literature Review

To understand how policy design factors impact individual vaccination uptake in the context of COVID-19, the following section will first outline the global COVID-19 vaccination policy landscape. Following this, the chapter presents behavioural models that explain vaccine acceptance patterns and synthesises empirical evidence on its determinants, specifically examining how policy stringency, agency, and individual characteristics shape vaccination decisions.

2.1. COVID-19 Policies around the World

When the COVID-19 pandemic emerged in 2020, governments around the world faced the challenge of developing and administering vaccines at scale, while simultaneously protecting the population through other policy interventions. Thus, governments put several interventions in place, which can be subdivided into non-pharmaceutical interventions (NPIs) and vaccination policies.

NPIs are public health measures designed to reduce disease transmission without the use of medical treatments. Before the first commercially approved vaccine became available in December 2020, governments started introducing a series of NPIs, such as mask mandates, which varied across countries due to differences in infrastructure and patterns of disease spread (Hale et al., 2021). Systematic reviews have confirmed the general effectiveness of NPIs in reducing COVID-19 incidence rates, although their impact depended on the stringency and framing of the interventions (Peters & Farhadloo, 2023). Despite their epidemiological benefits, NPIs, especially lockdowns, imposed social and economic costs. Onyeaka et al. (2021) highlighted that lockdowns disrupted food security, mental health, and economic activity, disproportionately influencing vulnerable populations. These adverse effects made governments recalibrate their strategies.

When the first COVID-19 vaccine was introduced, governments started shifting their focus towards large-scale vaccination campaigns, with NPIs remaining in place as a complementary measure. By the end of 2021, over 12 billion vaccines had been administered globally, reaching over 60% of the population (Tatar et al., 2022). During this time, governments also started rolling out booster vaccines, which were additional vaccine doses to maintain immunity. Similar to NPI policies, vaccine strategies varied significantly across countries. While some countries opted for universal vaccine mandates, others either left it entirely up to individuals or introduced targeted mandates for healthcare professionals or public service workers. In Europe, these divergences have been particularly apparent (see Figure 1).

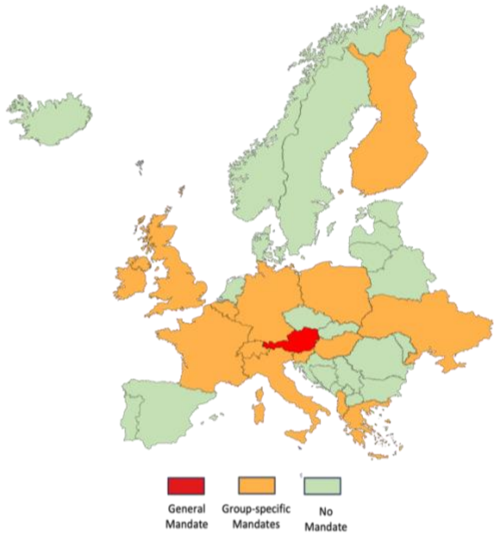

Figure 1 - Overview of European vaccine mandate policies, implemented at any point in time (Cameron-Blake et al., 2023)*

Across Europe, only Austria introduced a general mandate for a brief period, which applied to all individuals. Meanwhile, countries such as France or Germany restricted mandates to high-risk occupations, while other countries such as Spain or Denmark never imposed legal mandates (Cameron-Blake et al., 2023). In a cross-country study by Kuznetsova et al. (2022), it was observed that the introduction of vaccine mandates and COVID-19 certificates was associated with increasing vaccination rates, particularly among hesitant individuals. However, studies also highlight that the effect of mandates often diminished over time, with some countries experiencing only temporary increases in vaccination rates (Zhu et al., 2023). This implies vast levels of heterogeneity amongst the population, which requires further understanding of what motivates the individual uptake.

2.2. Behavioural Models of Vaccine Acceptance and Interventions

According to Michie (2022), behavioural determinants are crucial in analysing the individual willingness to get vaccinated, as health-related behavioural patterns such as vaccine hesitancy can arise from a complex interplay of individual beliefs and structural contexts. In recent years, several behavioural models have emerged, with the COM-B and the Health Belief Model (HBM) being among the most commonly used ones in the context of analysing vaccine uptake. The following section will outline both the COM-B and the HBM, ultimately leading up to the Behavioural Change Wheel (BCW), a commonly used policy design model for behavioural interventions.

The COM-B model, introduced by Michie et al. (2011), is a behavioural change framework which states that three essential elements: Capability, Opportunity, and Motivation, must align for individuals to adopt behavioural patterns such as getting vaccinated. Capability refers to the psychological and physical capacity to make informed decisions. Thus, hesitancy to get vaccinated could emerge when individuals lack knowledge or are exposed to misinformation, thereby undermining their psychological capability to evaluate vaccine safety and effectiveness (Kricorian et al., 2022). Opportunity captures exogenous conditions that affect behavioural actions, such as the ease of access to vaccination sites. According to Duffy et al. (2021), for instance, a lack of nearby COVID-19 vaccine appointment options can diminish the vaccine uptake in the long run. Finally, motivation incorporates both reflective attitudes and emotional responses, such as fear about side effects (Mohsin et al., 2022) or declining trust in institutions (Jennings et al., 2023).

Despite its popularity, the COM-B model only captures predispositions and therefore fails to consider individual attitudes towards health-related behaviour, such as perception. This dimension is captured by the HBM (Romate et al., 2022). Drawing on the Theory of Planned Behaviour, stating that behavioural actions are formed by intentions, norms and perceived behavioural control, the HBM emphasises the importance of subjective perceptions in decision-making scenarios (Ajzen, 1991). Thus, people are thought to engage in preventive health actions if, for example, they perceive themselves as susceptible to a condition or believe that the condition has serious consequences (Romate et al., 2022). This can be directly related to the COM-B model, as, for example, when people judge their personal risk of infection as low, the motivation to vaccinate often declines (Brewer et al., 2007). Conversely, perceived barriers, such as fear of side effects, can outweigh perceived benefits, resulting in hesitancy. Based on these models, behavioural interventions can be designed via the BCW. In this model, the components of the COM-B model are linked to 9 intervention functions (see Figure 2). Thus, while education, persuasion and incentivisation adhere to enhancing the opportunity dimension of the COM-B model, enablement, coercion, and training can foster motivation to engage in a certain behaviour. Additionally, individual capabilities are driven by modelling, environmental restructuring and restrictions (Michie et al., 2011).

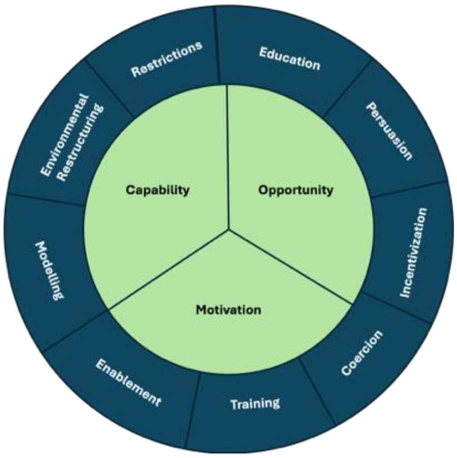

Figure 2 - The COM-B model and the Behaviour Change Wheel (Michie et al., 2011)*

During the COVID-19 pandemic, especially interventions targeting motivation and capabilities have been applied by governments (Chater et al., 2023; Silubonde-Moyana et al., 2023). Within this dimension, coercive interventions such as mask mandates were widely used and particularly effective in reducing disease transmission (Chung et al., 2021). As opposed to restrictions, which make certain options impossible, coercive interventions allow individuals a choice in compliance but attach consequences to non-adherence, for instance, facing penalties for not wearing a mask. Nevertheless, Andreas et al. (2022) observed in a scoping review that interventions which target the opportunity dimension of the COM-B model, such as awareness campaigns, can enhance the long-term effectiveness of interventions.

These observations emphasise the importance of examining the level of coerciveness, as the most popular intervention type, and the level of opportunity provision through agency, which is regarded as the intervention with the highest assumed long-term effectiveness. Furthermore, the observed heterogeneity stresses the need for understanding how these design choices interact with individual characteristics to shape vaccine acceptance.

2.3. Determinants of Vaccine Acceptance

The following section presents evidence on the factors that influence vaccine uptake. For this purpose, the effect of policy stringency, agency and individual-level characteristics on the willingness to get vaccinated will be analysed.

2.3.1. The Effect of Policy Stringency on Vaccine Acceptance

Policy responses can vary substantially depending on the level of stringency that governments choose to apply. Policy stringency describes the varying degree of policy intrusiveness and the coercive power applied to steer anticipated behaviour (Hood, 2007; Capano & Howlett, 2020). This variation is commonly captured through the differentiation between hard and soft measures (Banerjee et al., 2021). In the context of COVID-19, stringent or hard measures may include mask mandates or restrictions on movement, while non-stringent or soft measures might instead rely on behavioural nudges such as reminders (Dai et al., 2021) or social norms interventions (de Ridder et al., 2023). From the perspective of the COM-B model, stringent policies can be classified as either coercive or restrictive measures.

During the COVID-19 pandemic, policy stringency was captured by the Oxford COVID-19 Government Response Tracker (OxCGRT). By tracking a range of both NPIs and vaccination policies across 19 policy areas, including mask or vaccine mandates, the OxCGRT represents a standardised index for comparing policy stringency across countries (Hale et al., 2021). Figure 3 shows the OxCGRT across Europe in December 2021, highlighting variations in stringency across countries.

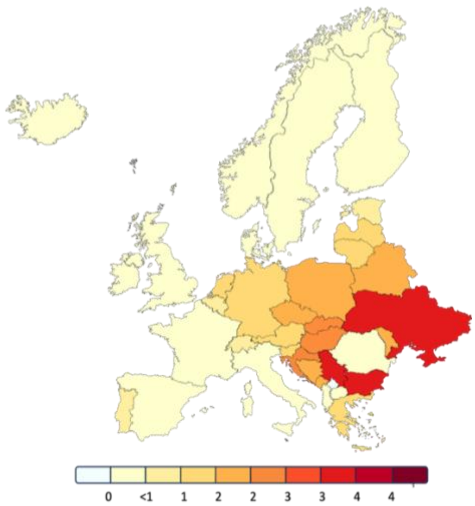

Figure 3 - OxCGRT across Europe (December 2021) (Hale et al., 2021)*

For example, Ukraine implemented some of the most stringent policies at that time, including border closures and suspensions of public transport. In contrast, the United Kingdom (UK) had by then lifted most restrictions, resulting in a lower stringency score. Public acceptance of stringent measures has fluctuated throughout the pandemic. Evidence from the UK indicates that at the beginning of the pandemic, a majority of the population supported stringent policies and even favoured extensions of restrictive measures, which later declined (Allington et al., 2023). Observed factors shaping public acceptance of stringent measures include both the perceived effectiveness of the policy (Koenig et al., 2024) and its level of intrusiveness (Betsch & Böhm, 2016), indicating the importance of personal deliberation for policy effectiveness, which can be incorporated into public policy via agency.

2.3.2. The Role of Agency in Public Policy

An often overlooked determinant of people's willingness to accept certain policies is agency, which is defined as *"…the individual's capacity to deliberate and determine what to choose"* (Vugts et al., 2020, p. 109). According to Vugts et al. (2020), agency is a component of autonomy, along with freedom of choice and the individual's ability to form a sense of identity via decisions. This definition was later refined by Dold and Lewis (2023), who stated that agency consists of both process freedom, the capacity to control choices, and opportunity freedom, the availability of choices. This categorisation was derived from Sen (2002), who stressed that both freedom of choice and the capacity to deliberate are structurally interrelated, thus, both aspects are necessary conditions for each other to result in individuals feeling a sense of agency.

In the context of public health, the concept of agency has been applied to shared decision-making between doctors and patients, resulting in the concept of patient agency. Lian et al. (2022) observed that providing individuals with the opportunity to actively participate in their health-related decisions, by proposing actions, opposing others, and expressing their values, enhances the likelihood of the individual's perceived ownership over their choices and long-term adherence to treatment options.

In practice, this can be applied via interventions such as Thinks, where people can engage in public discourse via citizen assemblies or other platforms (John et al., 2009). Based on this notion, other agency-enhancing policies have emerged, such as boost and nudge+ interventions. Unlike classical behavioural interventions, such as nudges, boosts aim to improve long-term decision-making competencies of individuals by actively conveying rules of thumb and reflective capabilities (Hertwig & Grüne-Yanoff, 2017). Nudge+ interventions combine the deliberative capabilities of boosts with the reflexive elements of nudges, resulting in a hybrid intervention that draws the attention of the decision-maker while allowing the individual to deliberatively act (Banerjee et al., 2022). These agency-enhancing interventions have been applied across several domains, ranging from sustainable diets (Thamer et al., 2024) to hospital hygiene (Van Roekel et al., 2022) and are often considered more ethical, as they not only allow people to actively engage in decision-making but also enhance the individual preference articulation by stimulating reflection and engagement (Sugden, 2018; Banerjee et al., 2022).

Nevertheless, there is a significant gap in the literature regarding the evaluation of different levels of agency in the field. Dold and Lewis (2023) argued that different levels of agency embedded into interventions could result in varying levels of engagement. Thus, too much choice freedom, for example, might result in choice overload, while too much process freedom could result in civic discontent or decision fatigue. Similar dynamics have been observed in the context of COVID-19 vaccination policies, for instance, Honora et al. (2022) observed that providing people with too much transparency on the vaccine can result in lower uptake. Nevertheless, the effects associated with varying levels of agency have not yet been explored in practice. Additionally, the role of covariates across both agency-enhancing and stringent measures has yet to be addressed.

2.3.3. Individual-level and Contextual Factors

Based on the literature, individual-level and contextual factors mediating COVID-19 vaccine uptake can be derived and subdivided into four domains: demographic characteristics, socio-political determinants, health-related behaviours, and trust in both the health intervention as well as the associated organisations (Thorpe et al., 2024).

Regarding demographics, gender and age in particular were observed to influence vaccine acceptance. Both Miller et al. (2022) and MacDonald et al. (2022) observed that women in particular expressed safety concerns about COVID-19 vaccine side effects. Regarding age, Lindholt et al. (2021) found that older adults were significantly more willing to be vaccinated than younger individuals, largely due to heightened perceptions of personal health risk. Similarly, Fazel et al. (2021) observed that vaccine acceptance increased with age among adolescents in England, with younger participants expressing low perceived vulnerability, reinforcing the differences in age-based risk perception as central to understanding vaccine preferences.

Regarding socio-political determinants, political partisanship has been considered a core mediator of vaccine acceptance across a variety of studies. Jones and McDermott (2022) found that Republicans were significantly more hesitant towards COVID-19 vaccines than Democrats, primarily driven by lower trust in the government and negative responses to scientific endorsements. Similarly, Papp and Nkansah (2023) found that Hungarian vaccine preferences followed party lines, with supporters of the ruling party favouring domestic vaccines.

Furthermore, previous health behaviour was observed to influence vaccine uptake during the pandemic. Prior engagement with preventive health actions, particularly past vaccination behaviour, strongly predicts acceptance of the COVID-19 vaccine. Crawshaw et al. (2022) found that individuals who regularly received seasonal influenza vaccines were significantly more likely to receive COVID-19 vaccinations.

Underlying these dynamics is the aspect of trust, which has been observed to influence how individuals make health-related decisions. In particular, Hartmann et al. (2024) demonstrated that trust in both the government and the vaccine mediates the relationship between policy stringency and vaccine acceptance, as low-trust individuals perceive stringent measures as particularly intrusive and unjustified. This suggests that trust may be the most significant factor driving vaccine acceptance.

2.4. The Present Study

Based on the literature review, the impact of policy-design factors on vaccine uptake remains inconclusive. Especially, the dimension of agency-enhancing interventions in the context of vaccination policies remains to be explored experimentally. To address these gaps, I propose the following general hypotheses:

GH1: Agency-enhancing interventions will increase the likelihood of individuals choosing a certain vaccination policy

GH2: Stringent measures will reduce the likelihood of choosing vaccination policies, while soft policies will increase it

GH3: Low trust will decrease the likelihood of choosing stringent policy measures

3. Survey Design and Data

My analysis was based on a large survey data set, which was collected in 2022. The data set is publicly available and was derived on June 25th 2025, from the OSF (https://osf.io/f86vz/). The following section will first outline the structure of the survey, subsequently present the structure of the conjoint analysis embedded into the survey, discuss the design of the interventions, provide descriptive statistics on the sample and elaborate upon the measured variables.

3.1. General Survey Design

The online survey study was administered in two waves (W1 & W2) in 2022 via Dynata, targeting respondents in Canada, France, Germany, Italy, Japan, the UK and the USA, thereby covering all G7 countries. The first wave took place between January and February 2022, while the second wave was conducted between March and May 2022. The survey consisted of three parts, which were ordered differently across waves: a conjoint analysis, a between-subject experiment on perceived vaccine effectiveness, and a between-subject experiment on nudge+ (see Appendix 12.1). In W1, the conjoint analysis was conducted first, followed by the experiment on vaccine effectiveness and the experiment on nudge +. In W2, the nudge+ experiment was conducted first, followed by the conjoint analysis and the vaccine effectiveness study. In the vaccine effectiveness experiment, participants were randomly given either numerical or relative descriptions of the booster vaccine efficacy before indicating their support for different vaccine promotion policies, ranging from less to more coercive. The between-subject experiment on nudge+ tested how reflective prompts influenced the willingness to comply with vaccine interventions by assigning participants to one of four conditions regarding vaccine appointment scheduling: control, nudge, reflection-only, or nudge+. Participants in the nudge+ and think groups were asked to reflect on proposed policies. Both the vaccine effectiveness and nudge+ experiments within the survey were previously analysed by Koenig et al. (2024) and Banerjee, John, et al. (2024), respectively. Koenig et al. (2024) examined how vaccine effectiveness shapes public support for stringent policies, while Banerjee, John, et al. (2024) investigated how reflection on default enrolment nudges affects vaccination intentions. However, the conjoint analysis within the survey remains entirely unexamined and will be addressed in the subsequent section.

3.2. Conjoint Analysis

A conjoint analysis is a survey-experimental technique that enables the causal estimation of individual preferences by examining how people make trade-offs between multiple attributes in complex decision-making scenarios (Hainmueller et al., 2014). This method is based on the notion that complex decision-making can be broken down into a set of factors, each of which contributes to an individual's preference (Luce & Tukey, 1964). These factors can be systematically combined, reflecting how people make trade-offs across multiple attributes of a choice.

In this study, the conjoint experiment was embedded into the above-mentioned survey design. This part of the survey aimed to investigate how various components of COVID-19 booster vaccination policies influenced public preference, thereby enabling a more granular analysis. For this purpose, participants were shown an introductory vignette (see Appendix 12.2) before having to choose between two policy options three consecutive times, which consisted of varying attribute levels (Option A and B). W1 employed a 3x3x2x2 factorial design, including four sets of attributes with different levels, which were randomly allocated across participants: scheduling (3 levels), reminders (3 levels), employee mandates (2 levels) and fines (2 levels), resulting in a total of 36 unique policy profiles (see Table 1).

Table 1 - Conjoint overview

Booster attributes	Wave 1	Wave 2
Scheduling	Self-schedule Clinic calls to schedule Call and discuss, then schedule	Call to offer to schedule not included Call to offer to schedule included
Reminder	No reminder Automatic reminder Call and discuss, then reminder	Automatic reminders not included Automatic reminders included
Information campaign	-	Not included Included
Employer mandates	No Yes	Not included Included
Government fines	No Yes	Not included Included
N	24,303	18,114

W2 employed a 2x2x2x2x2 binary factorial design, in which individuals were sequentially presented with three sets of two policy options, which consisted of 5 attributes, each having two levels. This change was designed to assess social norms as an additional policy option, while at the same time enabling a cleaner analysis via the binary level structure. After choosing between the policy options, individuals had to state their support for both policy options on a continuous scale from 1 to 10 in both waves, with 1 indicating minimal and 10 indicating maximum support.

3.3. Intervention Design

The experiment employed five different attributes, with varying levels. Here, interventions in the context of vaccine scheduling, reminders, campaigns, employee mandates and fines were tested, with interventions being presented differently across waves. Both scheduling- and reminder-related interventions aimed to test the impact of different levels of agency provision, while social norms, fines and mandates were incorporated to test the effect of policy stringency on policy choice. Across both waves, agency was provided by proposing that local health clinics would call individuals and deliver different levels of process facilitation.

In W1, scheduling included three levels with different degrees of agency-enhancement: self-scheduling, a call by a clinic to schedule an appointment and a call in combination with the opportunity to ask questions, followed by clinic-assisted scheduling. Here, self-scheduling of appointments was considered as the most agentic option because it maximises the opportunity freedom of individuals, allowing them to select convenient times, while at the same time providing them with moderate levels of process freedom, as they were entrusted direct involvement in the decision-making process. The call for scheduling by the health clinic was considered the least agentic option as individuals were automatically given an appointment on the phone, thereby mimicking a default intervention, while at the same time not considering any process facilitation measures. The third level provided a moderate degree of agency by stating that individuals will be called to schedule a vaccine appointment and, simultaneously, were given the opportunity to discuss questions. Although opportunity freedom was low in this intervention, the chance to engage in a dialogue was designed to enable participants to retain some decision-making power and enhance their agentic capabilities via process freedom. (see Appendix 12.3 for wording). In W2, which was designed as a binary choice setting across all interventions, individuals had the choice between receiving a call during which healthcare professionals offered to schedule a vaccine appointment and no support, with no support being considered the equivalent of self-scheduling. Here, the offer to schedule option represented a moderately high version of agency, as individuals still had the opportunity to engage in the appointment scheduling process. This was considered a higher degree of opportunity freedom facilitation compared to the call to schedule option from W1, as it implied that people had more freedom of choice when scheduling the appointment, since this service was only offered to them, thereby leaving them a higher degree of self-constitution (see Appendix 12.4 for agency-based categorisation).

In W1, reminder-based interventions were evaluated across three levels: no reminders, automatic reminders, and a call to discuss open questions, followed by automatic reminders. Here, no reminders represented a passive non-intervention that, while preserving autonomy and freedom from external influence, lacked both opportunity enhancement and process facilitation (Au et al., 2020). Despite this limitation, I argue that this intervention maintained higher agency than automatic reminders by preserving individuals' self-determination and avoiding interventions that operate through unconscious processes (Lewis & Holm, 2022). The third level of the reminder options entailed the highest level of agency by including a call to discuss any questions, followed by automatic reminders. This level can be classified as a nudge +, as it combines a nudge intervention, in this case the automatic reminders, with an element of deliberation, which was delivered via the call (Banerjee & John, 2023).

To assess the impact of policy stringency on vaccine uptake, three interventions were designed, varying in their level of stringency. The social norms campaign, which was only tested in W2, represented a soft policy intervention and proposed that the government would introduce an information campaign, stating how most people get vaccinated, representing a descriptive social norm (Legros & Cislaghi, 2020). Fines represented a moderately stringent intervention, as individuals could still choose not to comply by paying the fine, while mandates were the most stringent option available (Koenig et al., 2024). All interventions testing the effect of policy stringency on vaccine uptake were assessed in a binary manner across waves, either including or excluding the intervention in the policy option.

3.4. Descriptive Statistics

The final sample consisted of 42,417 participants, with 24,303 in W1 and 18,114 in W2. The gender ratio was approximately balanced in each wave and across the sample. Similarly, the nationality of participants was balanced, allowing a thorough evaluation of responses across countries (see Appendix 12.5). The high vaccination rates observed across both waves (80.3% complete doses) converge with the observed average vaccination rates in early 2022 across G7 countries (Mathieu et al., 2020). Age distribution shows a slight overrepresentation of middle-aged participants (35-54 years: 35.7%) compared to younger adults (18-34 years: 27.2%), which is typical of online panel surveys and reflects higher engagement rates among established adults. Overall, the sample characteristics provide a solid foundation for examining vaccination policy preferences across diverse demographic and national contexts.

3.5. Observed Variables

The original set-up of the experiment allowed individuals to choose a preferred policy option first and subsequently state their support on a scale from 1 – 10 for each of the two policy options across the three conjoint tasks. To assess the likelihood of choosing a certain policy option, the first measure was facilitated and treated as a binary variable called "*conjointchoice*", which was set equal to 1 if the profile was selected over its paired alternative and 0 if otherwise. This captures revealed preference in a forced-choice setting. The conjoint choice variable was selected instead of conjoint support because choice-based conjoint analyses closely approximate real-world decision making and are most commonly used within conjoint analysis research. Furthermore, the forced-choice format also provided cleaner identification of preference trade-offs compared to rating-based measures, which may be subject to individual differences in scale interpretation (Hainmueller et al., 2014).

The experimental set-up additionally recorded a wide range of covariates, which can be subdivided into demographic, social, health-related and political measurements. The demographic variables included measurements such as age, gender, level of education, country of origin and many more, which were coded as categorical variables. Social measures represented attitudes toward institutions and civic trust and were mainly captured by presenting individuals with a statement to which they could agree on a scale from 1 (strongly disagree) to 10 (strongly agree). Both health-related items, including previous health behaviours and attitudes toward medical interventions, and political variables, such as political affiliation, were also assessed on a scale from 0 to 10.

4. Analytical Strategy

Based on the data set, I conducted a conjoint analysis to explore individual preferences on COVID-19 booster vaccination policies. The following section will first elaborate on the derivation of the Average Marginal Component Effect (AMCE) across both waves and subsequently discuss the identification strategy and assumptions.

4.1. AMCE Calculations

To estimate the causal effect of each vaccination policy attribute on public preferences, I employed a conjoint analysis framework that calculates AMCEs. These measures represent the marginal effect of a particular attribute level on the probability that a respondent selects a policy profile, averaged over the distribution of all other attributes. This makes them particularly well-suited for capturing trade-offs in complex policy scenarios, where respondents evaluate multidimensional profiles simultaneously (Hainmueller et al., 2014). To implement this approach, I used Ordinary Least Squares (OLS) regressions.

For each wave, I estimated two models: (1) a pooled regression with no covariates and (2) a model including country fixed effects. The first model, which serves as the baseline, is formally specified as:

$$Y_{ij} = \beta_0 + \sum_k \beta_k * x_{ijk} + \varepsilon_{ij}$$

Here, Y_{ij} denotes the outcome (policy choice) for respondent i and profile j, x_{ijk} represents dummy variables for the levels of each attribute k, and ε_{ij} is the error term. These models are estimated with standard errors clustered at the respondent level to account for repeated measures within individuals, as each respondent evaluated multiple policy profiles.

Country fixed effects were included in the second model to account for unobserved heterogeneity across countries, such as baseline vaccine uptake or differences in exposure to public health measures. No control variables were included in the model, following an analysis using the Least Absolute Shrinkage and Selection Operator (LASSO). LASSO is a regression method that selects a subset of the most prognostically useful covariates by shrinking irrelevant coefficients toward zero (Tibshirani, 1996). This specification was determined in the Bayesian Information Criterion (BIC), Adaptive and Cross-validated form (Belloni et al., 2014). All models resulted in no additional controls being selected across waves, indicating that the conjoint attributes alone are sufficient to explain the observed effects (see Appendix 12.6 & 12.7).

All models across both waves derive the AMCE with self-scheduling and no reminders as the baseline in the relevant dimensions, as these were considered the most common policy options across all G7 countries in the context of COVID-19 booster vaccines (Savani et al., 2025). The primary identification of causal effects relies on the randomised structure of the conjoint design, but incorporating country fixed effects and clustered standard errors ensures that unobserved confounders do not drive estimates.

4.2. Identification Strategy and Assumptions

According to Hainmueller et al. (2014), three core assumptions must hold to derive causal estimates from the AMCE calculations: stability and no carryover effects, the absence of profile-order effects and the randomisation of profiles.

The stability assumption requires a respondent's potential outcome for any policy profile pair to depend only on the given attribute, presented in this specific task. To test the stability, the model was re-estimated across waves using three specifications: a linear probability, logistic regression and probit model. Each model regressed a binary attribute of the chosen profile on the full set of attribute-level dummies and country fixed effects, using robust standard errors clustered at the respondent level. Across all attributes, no differences in coefficients exceeded 0.006, and confidence intervals consistently overlapped (see Appendix 12.8). This suggests that the model choice does not influence the interpretation. To test for carryover or learning effects within the conjoint, choice rates were examined across the three tasks. Across waves and tasks, they were stable at 50%. The trend tests, regressing choice rates on task sequences, showed no significant evidence of fatigue effects.

The second assumption of conjoint analysis, the absence of profile-order effects, states that the order in which policy profiles are presented should not influence the individual's choice. To test this, the individual propensity to choose profile A (left-hand side) was estimated. This resulted in a statistically significant bias. Despite randomisation, profile A was chosen 26.6% of the time in W1 and 27.7% in W2, rather than the expected 50%, indicating a substantial order effect in both waves ($p < 0.01$). To assess whether this affects the main findings, the main model for both waves was re-estimated, including a profile order indicator, which did not affect the coefficients. This indicates that while respondents exhibited a systematic preference for profile B, this bias was orthogonal to the experimental treatments and did not compromise the causal estimates (see Appendix 12.9).

Finally, it is assumed that all attributes are allocated randomly across profiles to ensure exogeneity. In W1, all joint F-tests for attribute balance showed no significant associations ($p > 0.05$), demonstrating successful randomisation. In W2, joint F-tests indicated imbalances, primarily driven by country differences. However, when tested without country fixed effects, the pattern suggests these imbalances reflect respondent selection rather than randomisation failure. Taken together, it can be argued that the assumptions of conjoint analysis hold in this design.

5. Experimental Hypotheses

Drawing upon both the general hypotheses derived from the literature as well as the experimental design, I propose six experimental hypotheses.

GH1: Agency-enhancing interventions will increase the likelihood of individuals choosing a certain vaccination policy

The first general hypothesis states that agency-enhancing interventions will increase the likelihood of individuals choosing a certain vaccination policy. In the experimental context, the provided agency-intensity within the intervention was ranked as follows from highest to lowest: (1) Self-Scheduling, (2) Calling to offer to schedule, (3) Calling to schedule and discuss, (4) Calling to schedule (see Chapter 3.3). Thus, the following hypotheses can be derived:

> **H1:** Calling individuals to offer to schedule an appointment will increase the likelihood of choosing a vaccination policy as opposed to self-scheduling

Calling to offer to schedule was considered the 2nd most agency-enhancing intervention, while self-scheduling was considered the most agentic. Based on the literature review, I argue that, when compared to a slightly less agentic version, individuals would perceive the choice overload, emerging from completely agentic interventions, as more salient, and thus give up opportunity freedom for guidance.

> **H2:** Offering to answer people's questions before scheduling a vaccine appointment will increase the likelihood of choosing a vaccine policy compared to appointment scheduling via call (**H2a**) and to self-scheduled appointments (**H2b**)[1]

> **H3**: Offering to answer people's questions before sending vaccine reminders will increase the likelihood of choosing a vaccination policy compared to automatic reminders only (**H3a**) or to no reminders (**H3b**)[1]

Individuals are especially concerned about process facilitation when it comes to health-related decisions. Thus, I would assume, based on the literature, that people prefer the highest level of process freedom when facing decisions on scheduling and reminders, which is provided via the call to discuss questions.

GH2: Stringent measures will reduce the likelihood of choosing vaccination policies, while soft policies will increase it

[1] Pre-registeded with slight changes in wording on https://osf.io/f86vz/

Additionally, the experimental set-up assesses the effect of stringent and non-stringent policy measures on policy preference. Regarding soft policy interventions, the following experimental hypothesis was constructed:

> **H4**: Policies that include social norms messaging will increase support for vaccination policy compared to policies without such messaging.

In W2, social norms were tested as a soft measure to enhance vaccine uptake. In the context of COVID-19 vaccines, social norms campaigns have proven effective at promoting vaccination uptake (Korn et al., 2020; Moehring et al., 2023). W2 of the survey tests this by varying whether policy packages include a descriptive norm, emphasising that most people get the vaccine.

> **H5:** Policies that include coercive elements will reduce the likelihood of choosing the associated policy

Regarding stringent measures, both fines and mandates were tested across waves, which were thought to reduce public support due to their perceived intrusiveness.

GH3: Low trust will decrease the likelihood of choosing stringent policy measures

Finally, the literature suggests that the individual's willingness to engage in stringent measures will be moderated by the individual's trust level, as trust shapes the perceived legitimacy of interventions, resulting in the following hypothesis:

> **H6:** The effect of coercive vaccination policies on policy support will be moderated by individuals' trust in vaccines, such that among individuals with low vaccine trust, mandates and fines will have a negative effect on policy support and choice

In a study by Betsch and Böhm (2016), it was observed that compulsory vaccination policies can backfire among those with low vaccine confidence, leading to reduced willingness to vaccinate and lower support for such policies. The overall results and their implications on each experimental hypothesis will be presented in the subsequent section.

6. Results

The following section will outline the results across waves. Subsequently, a heterogeneity analysis will be conducted before the results will be put in the context of the hypotheses.

6.1. AMCE Calculation

To estimate the AMCE across both waves, I constructed two models with two specifications each using OLS regressions with robust standard errors clustered at the respondent level. Across model specifications, the coefficients changed slightly in W2 in the presence of country fixed effects, thus, coefficients from this model will be reported.

In W1, both clinic-assisted scheduling by itself (β=-0.058, p<0.01) and in combination with the option to discuss questions (β=-0.047, p<0.01) lowered the likelihood of policy choice compared to self-scheduling at a statistically significant level (see Appendix 12.10). Nevertheless, when using the clinic-assisted scheduling as a baseline, offering people to discuss their questions on the vaccine enhanced the likelihood of choosing the associated policy option by 1.1 percentage points (see Appendix 12.11). Regarding reminders, both automatic reminders by themselves (β=+0.115, p<0.01) and in combination with a call (β=+0.089, p<0.01) enhanced the choice probability compared to no reminders. While mandates had a small positive effect on policy choice at marginal statistical significance (β=+0.005, p<0.1), fines significantly reduced the likelihood of choosing the policy option by 8.7 percentage points, which was highly statistically significant.

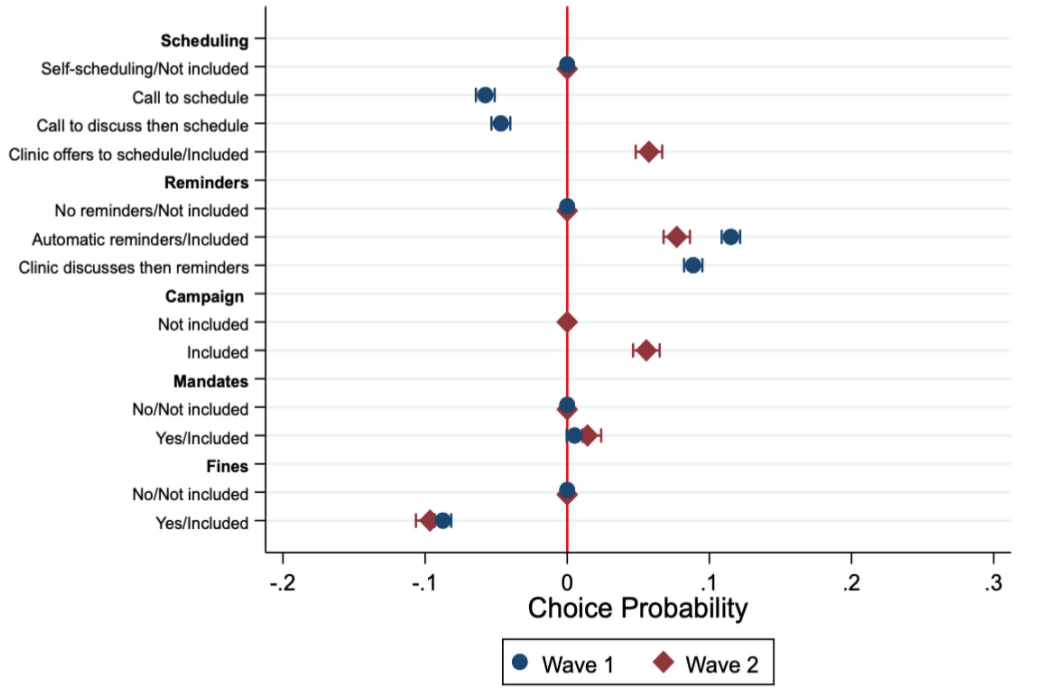

Figure 4 - AMCE across both waves using country fixed effects (see Appendix 12.10 & 12.12)

In W2, the call to offer to schedule enhanced the likelihood of choice by 5.8 percentage points at the 1% significance level. Automatic reminders remained positive (β=+0.077, $p < 0.01$), confirming the W1 findings. The presence of the newly introduced social norms campaign led to an increase in the likelihood of choice by 5.6 percentage points, also at a 1% significance level. The coercive policies revealed mixed results, with employer mandates exhibiting a small positive effect (β=+0.014, $p < 0.01$), while government fines remained strongly negative (β=-0.096, $p < 0.01$) (see Appendix 12.12).

When comparing both waves, most effects converge in the same direction, except for scheduling, leaving room for further exploration (see Figure 4).

6.2. Heterogeneity Analysis

Across both waves, heterogeneity was observed. The following section will focus on differences in policy responses based on gender, age, political orientation and trust in the vaccine (see Appendix 12.13).

First of all, there are individual differences across age groups. As the median age was 47 years across waves, age was converted into a binary variable, analysing individuals either above or below 50. For the scheduling interventions, participants in W1 in both age groups preferred self-scheduling over clinic-controlled scheduling, with older adults demonstrating slightly stronger opposition to clinic-controlled scheduling. When the scheduling intervention included the more deliberative components ("call to discuss then schedule"), older adults showed more negative responses (β=-0.062, $p<0.01$) compared to younger adults (β=-0.052, $p<0.01$). In W2, adults above 50 expressed much stronger support for the call for scheduling compared to younger adults. Across age groups, participants showed similar preferences for all other interventions (see Appendix 12.14 & 12.15).

Across genders, individuals showed similar preference directions but with different levels of magnitude. The largest difference across gender can be observed in the context of fines in W1, where men showed strong opposition (β=-0.112, $p<0.01$) while women had a lower probability of only 6.2 percentage points of choosing policy options associated with this attribute.

Political orientation also resulted in heterogeneous patterns. Respondents were categorised as left-wing (0-4 on the scale) or right-wing (7-10). While most preferences converged in the same direction, preferences differed in directions for mandates. While left-wing individuals in W1 showed positive responses (β =+0.041, $p<0.01$), right-wing individuals demonstrated opposition to mandates (β =-0.012 $p<0.01$). W2 confirmed these findings, although the coefficient for right-wing individuals was not statistically significant.

Trust in the vaccine resulted in high levels of heterogeneity, as respondents with low trust were more resistant to both mandates and fines (see Figure 5). In W1, such individuals were 15.6 percentage points less likely to support mandates and 23.1 percentage points less likely to support fines, while high-trust individuals had a higher likelihood of supporting mandates (β =+0.011, p<0.1) but opposed fines at a lower magnitude (β =+0.007, p<0.1). W2 revealed similar trends, with lower support for mandates (-7.5 percentage points) and fines (-13.0 percentage points) among low-trust individuals. These coefficients were significant at the 1 % level across waves.

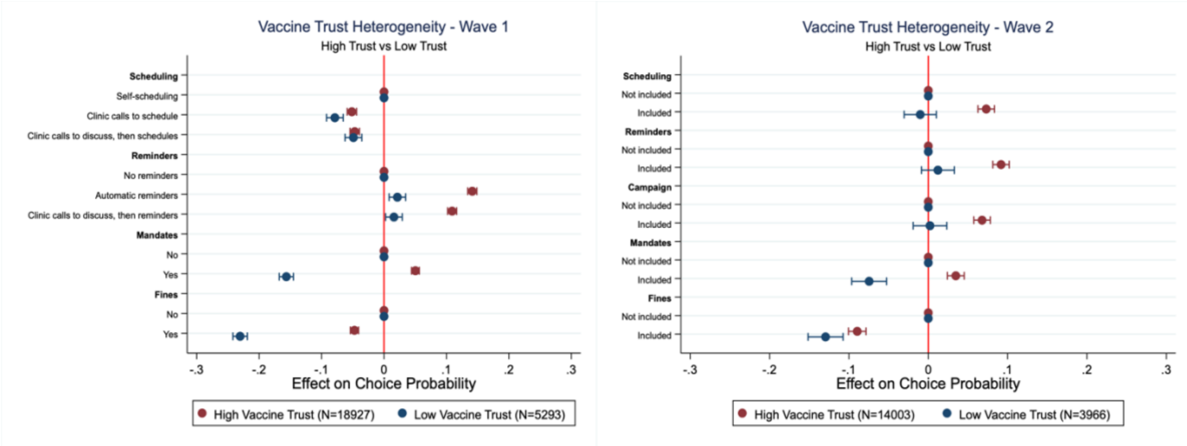

Figure 5 – Trust Heterogeneity (see Appendix 12.14 & 12.15)

Besides individual characteristics, some differences across countries were observed for both stringent (mandates and fines) and soft policies (scheduling assistance, automatic reminders, social norms). In terms of stringent measures, the UK and Japan showed the highest reactiveness to fines, while Germany and Italy most strongly preferred mandates. Regarding soft measures, both Germany and Japan showed the strongest support for the call to schedule interventions in W2, but at the same time, the strongest opposition in W1. Automatic reminders were consistently favoured across both waves by individuals from Germany, Japan and the UK, but at the same time, most opposed by US citizens. The social norms campaign is most favoured by UK citizens (see Appendix 12.16).

These implications of the results on the experimental hypotheses will be presented in the subsequent section.

6.3. Implications on the Hypotheses

Based on the results, implications on the hypotheses can be derived, focusing on the impact of varying levels of agency and stringency on vaccine uptake.

Table 2 - Hypotheses overview

Hypotheses	W1	W2
H1: Call to offer to schedule>Self-schedule	n.a.	0.058***
H2a: Call to schedule and discuss>Call to schedule	0.011***	n.a.
H2b: Call to schedule and discuss>Self-schedule	-0.047***	n.a.
H3a: Call and discuss, then reminder>Automatic reminders	-0.027***	n.a.
H3b: Call and discuss, then reminder>No reminder	0.089***	n.a.
H4: Social Norms => higher likelihood of policy choice	n.a.	0.056***
H5: Coercive elements => lower likelihood of policy choice	*Mandates:* 0.05* *Fines:* -0.087***	*Mandates:* 0.014*** *Fines:* -0.096***
H6: Coercive elements will be moderated by trust	*Mandates:* -0.156*** *Fines:* -0.231***	*Mandates:* -0.075*** *Fines:* -0.130***

Note. *p<0.1,**p<0.05,***p<0.01,n.a.=not applicable

i) Agency

It was observed that offering to schedule an appointment via a call increases the chance of selecting the policy option by 5.8 percentage points at the 1% significance level, providing strong support for **H1**.

In the first wave, the call to discuss option incorporated higher levels of process facilitation. It was observed that offering to answer individuals' questions before scheduling the appointment increased the likelihood of policy choice by 1.1 percentage points compared to offering a call for scheduling only (**H2a**), but reduced the likelihood by 4.7 percentage points when compared to self-scheduling (**H2b**). Taken together, these findings provide partial support for hypothesis 2.

In terms of reminders, it was observed that offering to answer individuals' questions before sending vaccine reminders increased the likelihood of policy choice by 8.9 percentage points compared to receiving no reminder (**H3b**), while it decreased the likelihood by 2.7 percentage points relative to receiving automatic reminders only (**H3a**), also providing mixed support for the hypothesis.

Overall, the survey provides mixed evidence on the role of agency in vaccine policies.

ii) Stringency

Regarding stringency, both one soft and two hard policy measures were tested, with the soft measure only being tested in W2. Here, the presence of a social norms campaign increased the likelihood of policy choice by 5.6 percentage points as opposed to no campaigns, thereby supporting this hypothesis (**H4**).

Stringent measures, represented by mandates and fines, resulted in mixed observations (**H5**). In W1, it was observed that mandates increase the likelihood of choosing a policy option by 5 percentage points at the 10% significance level, while fines reduced the likelihood by 7.8 percentage points at the 1% significance level. In W2, similar patterns were observed, both at the 1% significance level, indicating that mandates increase the likelihood of policy choice by 1.4 percentage points, while fines reduced the likelihood by 9.6 percentage points.

Finally, regarding the trust dimension, low trust was associated with a substantial decrease in support for coercive measures across waves. In W1, the presence of mandates reduced the probability of selecting the corresponding policy option by 15.6 percentage points, while the inclusion of fines led to an even greater reduction of 23.1 percentage points ($p < 0.01$). W2 confirmed these patterns at a different magnitude. Here, low trust decreased the likelihood of choosing mandate-based policies by 7.5 percentage points, and policies involving fines by 13 percentage points (**H6**). These results provide robust evidence that vaccine trust significantly moderates public acceptance of coercive interventions.

7. Robustness Checks

To strengthen the validity of the analysis, the model was re-estimated with the continuous support outcome as the dependent variable and in the binary choice setting with all control variables. Furthermore, a lexicographic preference analysis was conducted to further examine respondents' prioritisation patterns.

Across both the choice and support models, most coefficients converge in direction but differ in magnitude. This difference is likely to occur, as continuous scales capture the full intensity of preferences across a broader range while binary choice outcomes are constrained to probability changes (0-1), which compresses effect sizes even though both measures show consistent directional effects. The only difference can be observed regarding mandates in W1, which nevertheless does not present a threat to the validity of the model due to the low significance level (see Appendix 12.17). Overall, nearly all effects go in the same direction, indicating that vaccine choice also aligns with the general support for the interventions.

To validate the implications of the LASSO of no required covariates, the model was re-estimated with all control variables. In the presence of control variables, the coefficients changed slightly, nevertheless, this led to a drop in sample size by 33% in W1 and 44% in W2, thereby supporting the idea of a parsimonious model (see Appendix 12.18).

Finally, a lexicographic preference analysis examined whether respondents used simplistic decision rules by always choosing profiles with specific attributes (Hjortskov & Andersen, 2024). Such behaviour biases AMCE estimates and, like profile order effects, indicates cognitive shortcuts. W1 showed high lexicographic rates (59% for 3-level attributes, 12-17% for binary), dropping to 4.5-6.8% in W2. The 60-64% decrease for comparable binary attributes suggests genuine behavioural change toward more sophisticated decision-making (see Appendix 12.19).

8. Discussion

This study provides insights into the impact of varying levels of agency and policy stringency on the individual willingness to choose vaccine-related policy measures. The following section will embed the findings into a theoretical context:

i) The impact of agency on policy choice

In the study, it was observed that preferences for agentic options depended on the presented alternatives, both for scheduling and reminders. Regarding scheduling, participants preferred self-scheduling over both clinical assistance options with low opportunity freedom in W1. However, in W2, when choosing between clinical assistance with higher levels of opportunity freedom and self-scheduling, they preferred assistance despite reduced opportunity freedom. This pattern reveals that individuals are willing to trade some opportunity freedom for enhanced process freedom when the alternative is complete self-reliance without support. Conversely, when more controlling alternatives are available, individuals prioritise maintaining their opportunity freedom. For reminders, participants consistently preferred automatic reminders despite their low agency.

The reactiveness of individuals to reductions in opportunity freedom regarding scheduling resonates with the literature on shared decision-making in healthcare. Lian et al. (2022) demonstrated that patients value freedom of choice, particularly in the context of health-related decisions, due to the deeply personal nature of health trade-offs that only individuals can evaluate based on their perceptions, which aligns with the HBM (Romate et al., 2022). The preference of individuals for automatic reminders with low agency enhancement suggests that the individuals' preference for agency also depends on the nature of the choice, thereby confirming the assumptions on agency in the field by Dold and Lewis (2023). According to Peterson et al. (2021), individuals often delegate facilitative responsibilities, such as receiving reminders, to others, while retaining ultimate authority over substantive choices. This pattern of selective delegation also aligns with bounded rationality principles, where individuals optimise cognitive resources by accepting external delegation for lower-stakes decisions (Gigerenzer & Gaissmaier, 2011). Thus, the findings suggest that individuals value agency not in absolute terms, but relative to the perceived alternatives and individually assigned value of the decisions.

ii) The impact of stringency on policy choice

Regarding the stringency dimension, one soft (campaign) and two stringent measures (mandates and fines) were tested. The campaign increased the likelihood of policy choice, which was in accordance with the literature. In the case of the stringent measures, diverging choice patterns were observed. While the presence of mandates enhanced the likelihood of policy choice, fines led to a decrease. These differences could be explained by the framing, associated legitimacy and ethical coherence of both types.

First, regarding framing, it can be argued that both stringent measures resulted in different kinds of perceived losses. While both fines and mandates resulted in perceived costs, these costs were only implied in the mandate intervention, whereas they were specifically mentioned for the fines intervention and of monetary nature. Research by Druckman (2022) on COVID-19 policy compliance found that people were more willing to accept access restrictions than monetary penalties. This aligns with the concept of loss aversion, stating that individuals perceive losses at a higher magnitude than gains (Kahneman & Tversky, 1979).

Furthermore, the perceived legitimacy of both stringent measures differed. Mandates, particularly employer mandates, operate within existing institutional structures and professional relationships. Employees already accept various workplace requirements, from dress codes to safety training, making vaccine mandates feel like a natural extension of employer authority to ensure workplace safety (Dubé & MacDonald, 2022). Moreover, a stream of literature indicates that both measures differ in terms of their perceived effectiveness. A systematic review by Liu et al. (2023) found that employment requirements consistently outperformed financial penalties in both immediate uptake and sustained compliance.

Moreover, there could have been differences in the perceived ethical coherence of both stringent measures. Canning et al. (2022) found that mandates are often perceived as more ethically legitimate, as they are often associated with serving the public good by protecting vulnerable members of society.

Overall, the findings of this part of the study suggest that individuals generally prefer soft measures, but their effectiveness depends on the context of the intervention.

iii) The impact of trust on stringent policy uptake

In this study, it was observed that low levels of trust in the vaccine reduced the likelihood of policy choice regarding stringent measures. Individuals with low trust were 7.5–15.6 percentage points less likely to choose options with mandates and 13.0–23.1 percentage points less likely to choose those with fines across waves. These findings are widely supported by the literature on vaccine uptake.

Larson et al. (2018) found that when people doubt the quality or risks associated with a vaccine, their willingness to comply with mandates declines, even when such measures are implemented for public health reasons. Similarly, Sapienza and Falcone (2022) showed that trust is not only associated with one's personal decision to vaccinate but also with their acceptance of broader policy interventions, including coercive or punitive strategies. A lack of trust can be influenced by perceived insufficient transparency, inconsistent messaging, or a history of overlooked community concerns. Thus, stringent measures imposed in low-trust settings may backfire, fostering greater hesitancy or resistance (Adhikari et al., 2022). Therefore, effectively promoting stringent vaccination policies requires building and maintaining trust through transparent communication and community engagement.

In summary, building trust in the vaccine is critical for the success of mandates and fines as public health measures. Without sufficient trust, these policies are much less likely to achieve high uptake.

9. Limitations

The evaluation entails some limitations regarding the experimental design, sample and context. Regarding the experimental design, three limitations can be identified. First of all, the experiment was designed in accordance with a forced-choice conjoint design, thereby forcing people to choose between two policy options. As the experimental design relied exclusively on stated preferences rather than revealed behaviour, there is a potential discrepancy between participants' hypothetical policy choices and their actual vaccination decisions, which may limit the external validity of the finding. While participants indicated which policy packages they preferred, it cannot be verified whether these expressed preferences would translate into real-world compliance. In this sense, the study does also not account for the level of perceived agency and solely relies on a rudimentary model of provided agency. Furthermore, despite being able to control for spillover effects from previous choices within the conjoint task, spillovers from previous parts of the experiment were not captured by the design due to the different nature of the tasks.

Regarding the sample, the experiment was conducted only across a G7 sample, which limited the observed sample to a WEIRD population (Western, Educated, Rich, Industrialised, Democratic). This could have diminished the external validity of the study, as it only captured effects across a culturally limited sample. In a systematic review by Solís Arce et al. (2021), it was observed that vaccine acceptance rates were substantially higher across Low- and Middle-Income Countries (LIMCs) as opposed to developed nations, which was primarily driven by different levels of trust in institutions and political polarisation regarding vaccines across nations. Additionally, the selection of participants via Dynata could have induced selection bias across the sample. Internet-based sampling could have systematically excluded individuals with limited digital access, thus, for instance, economically disadvantaged groups who are often most vulnerable to infectious diseases (Hargittai, 2020). Moreover, the cognitive burden imposed by evaluating six policy profiles with multiple attributes may have triggered satisficing behaviour, where respondents use simplifying heuristics rather than carefully weighing all attributes, which was also indicated by the profile order effects and lexicographic patterns.

Finally, there are contextual limitations to the study. First of all, the study was conducted in the context of booster vaccines. Thus, at this point in time, a large share of the G7 population had already received their first vaccinations, as underlined by the 80.7% vaccination rate across the sample. Therefore, the sample could not capture the attitudes of truly hesitant individuals sufficiently. Furthermore, the individual attitudes could have been influenced by recent developments regarding the pandemic spread in early 2022. Towards the end of 2021, a new COVID-19 variant called Omicron had emerged, which led to an aggravated course of the disease. This could have inflated the individual's willingness to accept certain vaccination policy measures due to a heightened fear of infection.

10. Policy Implications and Concluding Remarks

Overall, this study examined the impact of policy design factors, in particular varying levels of stringency and agency, on the individual willingness to choose certain vaccination policies. In terms of agency, it was observed that individuals are willing to trade some opportunity freedom for enhanced process freedom when the alternative is complete self-reliance without support. Conversely, when more controlling alternatives are available, individuals prioritise maintaining their opportunity freedom even at the cost of competence support. Regarding stringency, it was observed that people liked soft policies and disliked stringent policies, but the policy uptake for stringent policies included high levels of heterogeneity, primarily driven by differences in vaccine trust. All these observations have to be treated with caution, as they were recorded in a pandemic setting with an emphasis on the booster vaccines and only measured stated preferences. Furthermore, the level of perceived agency remains to be explored. Nevertheless, some policy implications can be derived for future vaccination policies and general pandemic preparedness. First of all, agency-enhancing interventions have high potential in both pandemic-related and general vaccination policy settings to enhance the individual willingness to engage in the policy. Nevertheless, they should consider the individual's opportunity freedom in particular, as individuals are unwilling to relinquish this freedom without a slight reduction in opportunity freedom, which can be balanced by guidance. Moreover, it can be inferred that individuals prefer soft policy measures, whereas stringent policy measures necessitate a heightened sense of trust among the population for public acceptance.

These findings could potentially contribute to future pandemic policy design measures. Nevertheless, long-term effects of agency-enhancing policy interventions remain yet to be explored, while the presented categorisation of agency-enhancing interventions can be seen as rather preliminary than set. This leaves room for further exploration on this topic to design pandemic protection plans which are not only effective but also ethically desirable.

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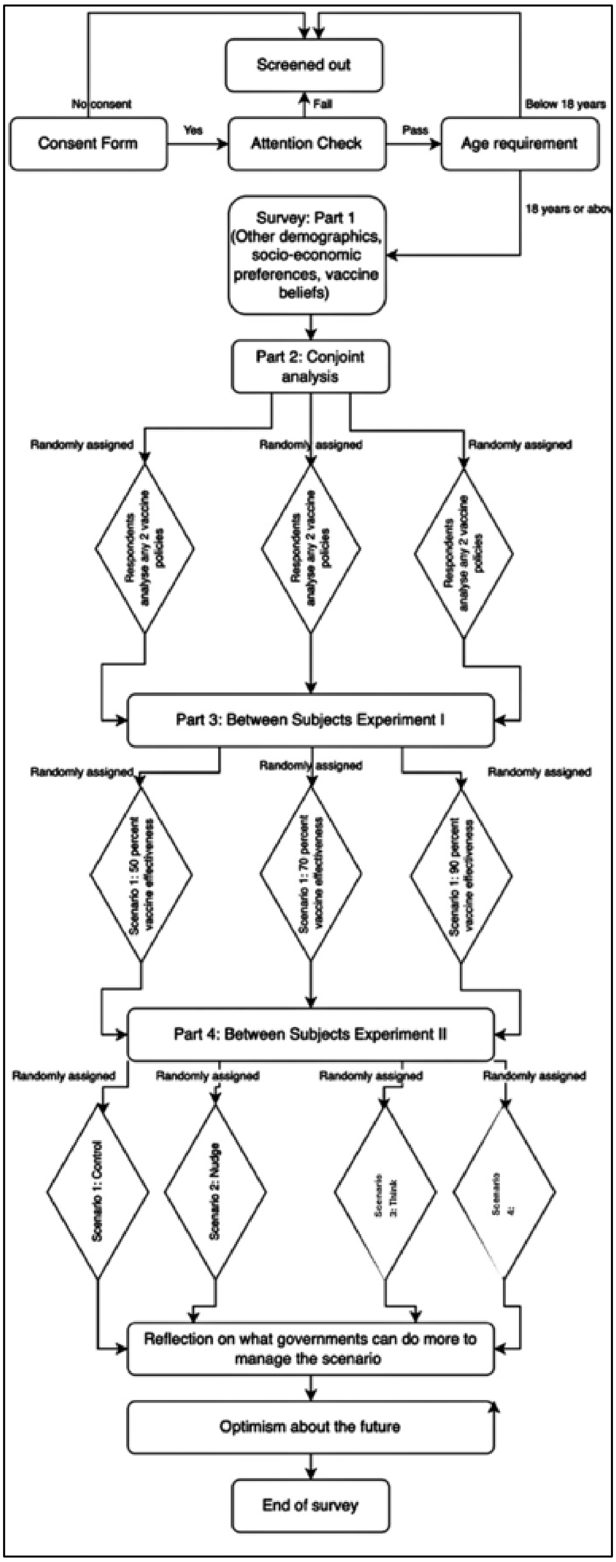
12. Appendix

12.1. Experimental Flow



Appendix Figure 1 – Survey Structure Wave 1 (Savani et al., 2025, p. 6)

12.2. Conjoint Introductory Vignette

We are interested in knowing what you think the government should do about COVID-19 vaccines. *Recently boosters are being offered by public health authorities to citizens to increase protection against the novel coronavirus and COVID-19.* *Imagine that, later in the year, your government will introduce a new vaccine policy that promotes boosters to protect the public from getting COVID-19 from new variants of the coronavirus.* *To gauge your views, we will show you several pairs of hypothetical government policies about COVID-19 vaccines. For each pair of hypothetical vaccine policies, please think about which vaccine policy you prefer. There are no 'right' or 'wrong' answers. Please answer as honestly as you can.*

Appendix Figure 2 - *Introductory vignette*

12.3. Intervention Design

Appendix Table 1 - Intervention Design with exact wording

Vaccine attributes	Wave 1	Wave 2
Scheduling	*- Self-schedule:* Self-scheduled appointments *- Clinic calls to schedule:* Your local health clinic will call you to schedule an appointment *- Call and discuss, then schedule:* Your local clinic will call you to discuss any questions you may have about the booster and will then schedule an appointment	Local health clinics will call every adult to offer to schedule an appointment for them to get this new booster *- Included* *- Not Included*
Reminder	*- No reminder:* You will not receive any reminders *- Automatic reminder:* You will receive automatic reminders *- Call and discuss, then reminder:* Your local clinic will call you to discuss any questions you may have about the booster and will then send you automatic reminders	Local health clinics will automatically send every adult a text message to remind them that their dose of this new booster is ready *- Automatic reminders not included* *- Automatic reminders included:*
Information campaign	*Not covered in wave 1*	The government will launch an advertising campaign that emphasises how most people will likely choose to get this new booster *- Not included* *- Included*
Employer mandates	Will employers be allowed to require that employees must receive the booster? *- No* *- Yes*	Employers will be allowed to require their employees to get this new booster *- Not included* *- Included*
Government fines	Will the government issue fines if you do not receive your booster when eligible? *- No* *- Yes*	Eligible adults will be fined if they do not get this new booster *- Not included* *- Included*
N	24,303	18,114

12.4. Agency ranking

Appendix Table 2 - Descriptive statistics across waves

Attributes	Wave	Opportunity Freedom	Process Freedom
Scheduling			
(1) Self-scheduling	W1 & W2	High	Moderate
(2) Call to offer to schedule	W2	Moderate	Moderately High
(3) Call and discuss, then schedule	W1	Low	High
(4) Call to schedule	W1	Low	Low
Reminders			
(1) Call to discuss, then reminders	W1	Moderate	High
(2) No reminders	W1 & W2	High	Low
(3) Automatic reminders	W1 & W2	Low	Low_

Note. This table presents the preliminary structure of agency incorporation into the different policy measures, displayed from highest to lowest agency provision. This categorisation is largely based on the associated literature by Dold and Lewis (2023) and Sen (2002) and primarily focusses on the level of provided agency, based on theory

12.5. Descriptive Statistics

Appendix Table 3 - Descriptive statistics across waves

Variable	Category	Wave 1 N	Wave 1 %	Wave 2 N	Wave 2 %	Total N	Total %
Gender	Female	12,454	51.2	9,399	51.9	21,853	51.5
	Male	11,734	48.3	8,638	47.7	20,372	48.0
	Other	115	0.5	77	0.4	192	0.5
Age	18-34	6,638	17.3	4,906	27.1	11,544	27.2
	35-54	8,643	35.6	6,518	36	15,161	35.7
	55-64	3,911	16.1	2,976	16.4	6,887	16.2
	65+	5,111	21.0	3,714	20.5	8,825	20.8
Education	Higher education	7,200	29.6	4,010	22.1	11,210	26.4
	No higher education	17,103	70.4	8,871	49.0	25,974	61.2
	N/A	0	0.0	5,233	28.9	5,233	12.3
Country	Canada	3,470	14.3	2,566	14.2	6,036	14.2
	France	3,485	14.3	2,623	14.5	6,108	14.4
	Germany	3,485	14.3	2,568	14.2	6,053	14.3
	Italy	3,487	14.3	2,565	14.2	6,052	14.3
	Japan	3,421	14.1	2,674	14.8	6,095	14.4
	UK	3,472	14.3	2,552	14.1	6,024	14.2
	USA	3,483	14.3	2,566	14.2	6,049	14.3
Trust in vaccine	High	18,945	78	14,052	78	33.007	78
	Low	5,284	22	4,037	22	9321	22
	N/A	74	0.0	25	0.0	98	0.0
Vaccine Status	Complete dose	19,606	80.7	14,476	79.9	34,082	80.3
	No dose	3,195	13.1	2,390	13.2	5,585	13.2
	Partial dose	1,463	6.0	1,239	6.8	2,702	6.4
	N/A	39	0.2	9	0.0	48	0.1

Note. This table presents the demographic distribution of the data. The sample consists of 42,417 individuals across 7 countries.

12.6. LASSO Wave 1

Appendix Table 4 - LASSO Wave 1

	(1) CV	(2) BIC	(3) Adaptive
Scheduling			
Clinic schedules	x	x	x
Clinic discusses then schedules	x	x	x
Reminders			
Automatic reminders	x	x	x
Clinic discusses then reminders	x	x	x
Mandates	x	x	x
Fines	x	x	x
Country effects	x	x	x
Constant	x	x	x

Note. Variable selection via LASSO regularization with Cross-Validation (CV), Bayesian Information Criterion (BIC), and Adaptive methods. Models tested 106 potential control variables including demographics, attitudes, and COVID-19 experiences. Checkmarks indicate variables selected by each method. All conjoint attributes were retained across methods. Clustered standard errors by respondent

12.7. LASSO Wave 2

Appendix Table 5 - LASSO Wave 2

	(1) CV	(2) BIC	(3) Adaptive
Call to offer to schedule	x	x	x
Automatic Reminders	x	x	x
Social Norms	x	x	x
Mandates	x	x	x
Fines	x	x	x
Country fixed effects	x	x	x
Constant	x	x	x

Note. Variable selection via LASSO regularization with Cross-Validation (CV), Bayesian Information Criterion (BIC), and Adaptive methods. Models tested 106 potential control variables including demographics, attitudes, and COVID-19 experiences. Checkmarks indicate variables selected by each method. All conjoint attributes were retained across methods. Clustered standard errors by respondent

12.8. Model Robustness checks

Appendix Table 6 - Different Model Specifications across waves

	(1) OLS		(2) Probit		(3) Logit	
	W1	W2	W1	W2	W1	W2
Schedule						
Clinic schedules	-0.058	n.a.	-0.058	n.a.	-0.059	n.a.
Clinic discusses then schedules	-0.047	n.a.	-0.047	n.a.	-0.048	n.a.
Clinic offers to schedule	n.a.	0.058	n.a.	0.058	n.a.	0.059
Reminders						
Automatic Reminders	0.115	0.077	0.117	0.078	0.117	0.078
Clinic discusses then reminders	0.089	0.056	0.090	0.056	0.090	0.057
Mandates	0.005	0.014	0.005	0.014	0.005	0.015
Fines	-0.087	-0.097	-0.089	-0.098	-0.089	-0.098

Note. Coefficients represent average marginal component effects (AMCEs). All models include country fixed effects and use robust standard errors clustered at the respondent level. Maximum difference refers to the largest absolute difference in coefficients across the three models for any attribute within each wave, W1 = wave 1, W2 = wave 2

12.9. Profile-order analysis

Appendix Table 7 - Profile order effect analysis

	(1) Wave 1	(2) Wave 2
Panel A:		
Profile		
Profile A selection rate	0.266	0.277
Expected rate (H0)	0.500	0.500
Deviation from expected	-0.234***	-0.233***
T-statistic	-229.1	-184-2
p-value	< 0.01	< 0.01
Panel B:		
Impact on Treatment Effect		
Schedule (Δ in coefficients)		
Clinic schedules	0.0005	n.a.
Clinic discusses then schedules	0.0001	n.a.
Clinic offers to schedule	n.a.	0.0004
Reminders		
Automatic Reminders	-0.0004	0.0007
Clinic discusses then automatic reminders	-0.0006	n.a.
Mandates	-0.000	-0.001
Fines	0.0001	0.0004
Maximum change Δ	0.0006	0.0001
Profile order β	0.068***	0.105***
	(0.004)	(0.005)
N	24,220	17,969

Note. Panel A shows test of H0: Pr(choose Profile A) = 0.5. Panel B shows attribute coefficients with and without controlling for profile order. Standard errors for profile order coefficient in parentheses, *$p<0.1$, **$p<0.05$, ***$p<0.01$.

12.10. AMCE Wave 1 calculation (Self-scheduling as baseline)

Appendix Table 8 - Average Marginal Component Effect Wave 1

	(1) Pooled regression	(2) Country Fixed Effects
Schedule		
Clinic schedules	-0.058***	-0.058***
	(0.003)	(0.003)
Clinic discusses then schedules	-0.047***	-0.047***
	(0.003)	(0.003)
Reminders		
Automatic Reminders	0.115***	0.115***
	(0.003)	(0.003)
Clinic discusses then automatic reminders	0.089***	0.089***
	(0.003)	(0.003)
Mandates	0.005*	0.005*
	(0.003)	(0.003)
Fines	-0.087***	-0.087***
	(0.003)	(0.003)
Constant	0.502***	0.501***
	(0.004)	(0.004)
N	144,540	144,540
R Squared	0.020	0.020

Note. Standard errors in paramtheses and clustered by respondent id. Baselines: self-scheduling, no reminders, No Fines, No Mandates *p<0.1, **p<0.05, ***p<0.01

12.11. AMCE Wave 1 Calculation (adjusted baselines)

Appendix Table 9 - Average Marginal Component Effect on Wave 1 (new baseline)

	(1) Pooled regression	(2) Country Fixed Effects
Schedule		
Self-Scheduling	0.058***	0.058***
	(0.003)	(0.003)
Clinic discusses then schedules	0.011***	0.011***
	(0.003)	(0.003)
Reminders		
No reminders	-0.115***	-0.115***
	(0.003)	(0.003)
Clinic discusses then automatic reminders	-0.027***	-0.027***
	(0.003)	(0.003)
Mandates	0.005*	0.005*
	(0.003)	(0.003)
Fines	-0.087***	-0.087***
	(0.003)	(0.003)
Constant	0.559***	0.559***
	(0.003)	(0.004)
N	144,540	144,540
R Squared	0.020	0.020

Note. Standard errors in parantheses and clustered by respondent id. Baselines: automatic scheduling, automatic reminders, no mandates, no fines, *p<0.1, **p<0.05, ***p<0.0

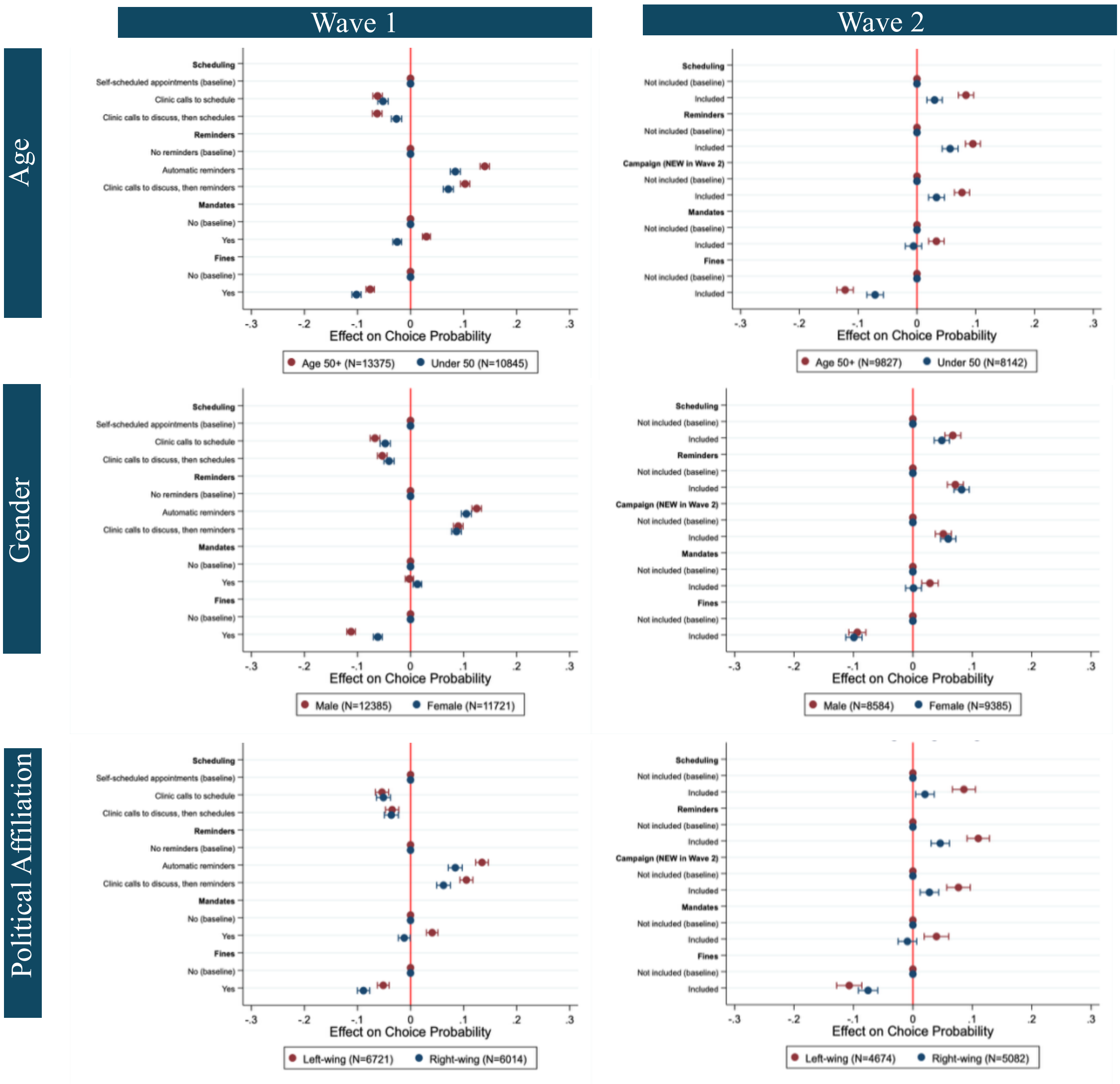
12.12. AMCE Wave 2 Calculation (Self-scheduling as baseline)

Appendix Table 10 - Average Marginal Component Effect on Choice of Vaccination Policies (Wave 2)

	(1) Pooled regression	(2) Country Fixed Effects
Schedule	0.043***	0.058***
	(0.004)	(0.005)
Reminders	0.062***	0.077**
	(0.004)	(0.005)
Campaign	0.041***	0.056***
	(0.004)	(0.005)
Mandates	-0.001	0.014***
	(0.005)	(0.005)
Fines	-0.111***	-0.097***
	(0.005)	(0.005)
Constant	0.493***	0.455***
	(0.001)	(0.004)
N	106,082	106,082
R Squared	0.008	0.009

Note. Standard errors in parentheses and clustered by respondent id. Baseline: self-scheduling, no reminders, no campaign, no mandates, no fines, *p<0.1, **p<0.05, ***p<0.01

12.13. Heterogeneity Figure



Appendix Figure 3 - Heterogeneity Analysis across waves

12.14. Heterogeneity Analysis Wave 1

Appendix Table 11 - Heterogeneity Analysis Wave 1

Attributes	Male	Low Education	Age 50+	Right-wing	Low Trust
Clinic schedules	-0.067***	-0.052***	-0.062***	-0.051***	-0.079***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.007)
Clinic discusses then schedules	-0.053***	-0.044***	-0.063***	-0.036***	-0.049***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.007)
Automatic reminders	0.125***	0.120***	0.140***	0.084***	0.021***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Clinic discusses then automatic reminders	0.090***	0.091***	0.103***	0.062***	0.016**
	(0.005)	(0.004)	(0.004)	(0.004)	(0.007)
Mandates	-0.002	0.004	0.030***	-0.012**	-0.156***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.006)
Fines	-0.112***	-0.082***	-0.076***	-0.089***	-0.221***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.006)
Constant	0.519***	0.493***	0.477***	0.520***	0.709***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.008)
N	76,619	101,694	79,414	103,895	31,393
R-squared	0.027	0.019	0.024	0.022	0.083

Note. Standard errors in parentheses. Standard errors clustered by respondent. Country fixed effects included. Reference groups: Female, High Education, Age <50, Left-wing (0-4), High Trust, * p < 0.10, ** p < 0.05, *** p < 0.01

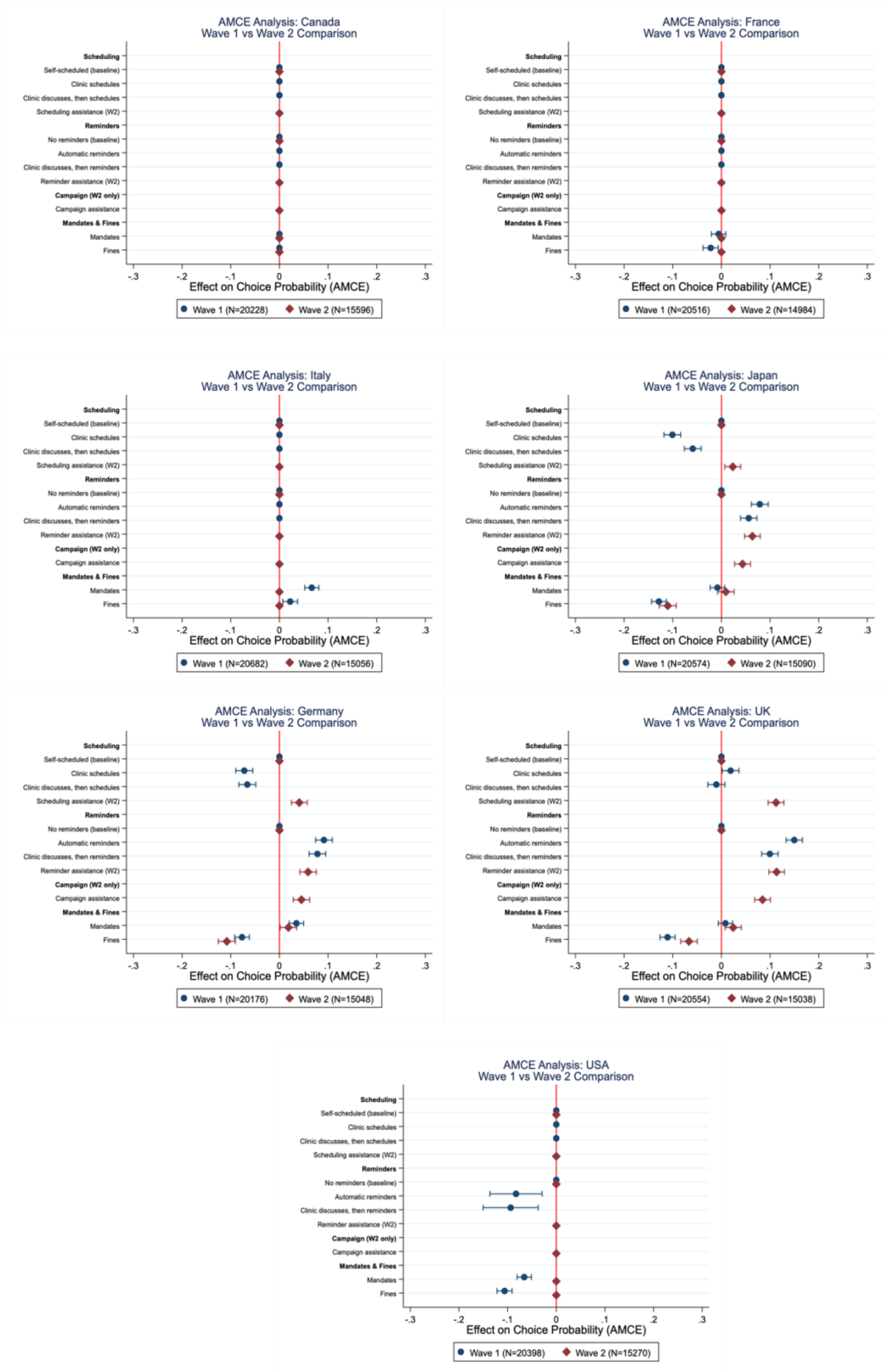
12.15. Heterogeneity Analysis Wave 2

Appendix Table 12 - Heterogeneity Analysis Wave 2

Attributes	Male	Low Education	Age 50+	Right-wing	Low Trust
Schedule	0.067***	0.057***	0.083***	0.020**	-0.010
	(0.007)	(0.006)	(0.007)	(0.005)	(0.010)
Reminders	0.071***	0.079***	0.095***	0.046***	0.012
	(0.007)	(0.006)	(0.007)	(0.005)	(0.011)
Campaign	0.051***	0.052***	0.077***	0.028***	0.002 (0.011)
	(0.007)	(0.006)	(0.007)	(0.005)	
Mandates	0.029***	0.014**	0.033***	-0.009	-0.075***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.011)
Fines	-0.094***	-0.096***	-0.122***	-0.075***	-0.130***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.011)
Constant	0.450***	0.456***	0.437***	0.467***	0.579***
	(0.006)	(0.005)	(0.005)	(0.004)	(0.010)
N	50,760	82,494	58,000	78,414	23,184
R-squared	0.009	0.008	0.015	0.008	0.009

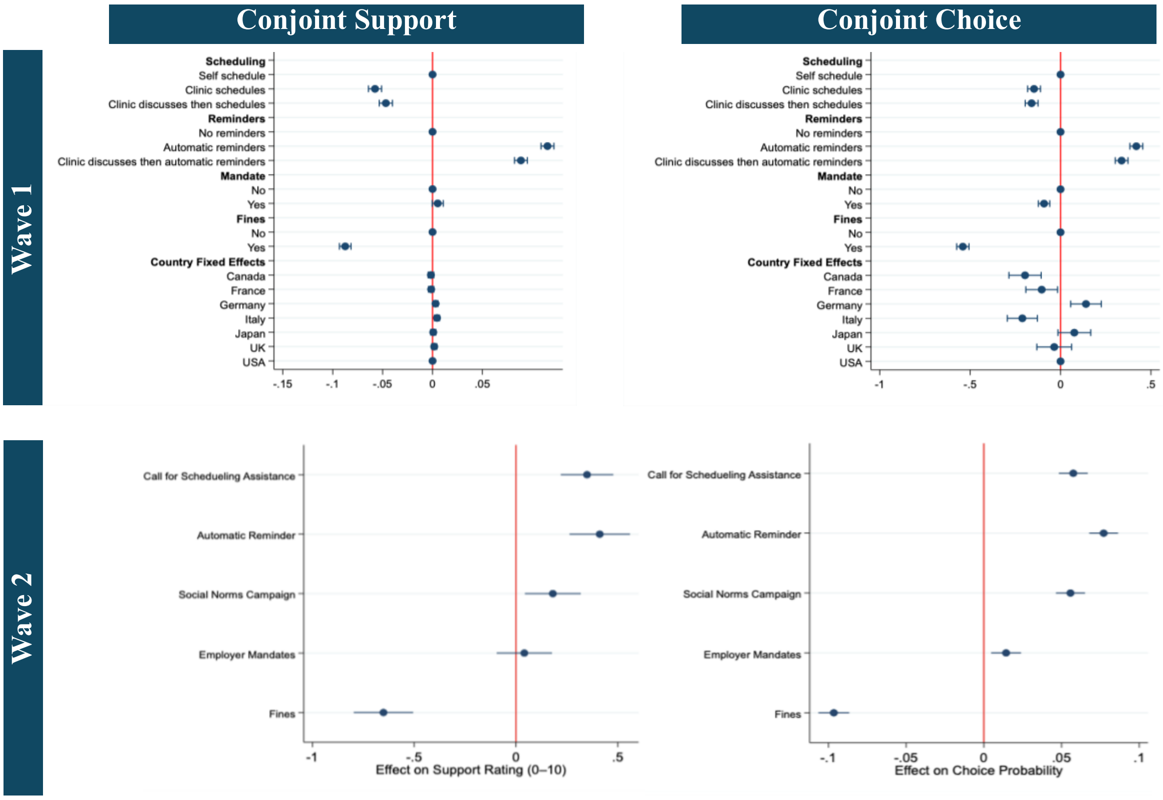
Note: Standard errors in parentheses. Standard errors clustered by respondent. Country fixed effects included. Reference groups: Female, High Education, Age <50, Left-wing (0-4), High Trust, * p < 0.10, ** p < 0.05, *** p < 0.01

12.16. Country-level heterogeneity



Appendix Figure 4 - Country-level heterogeneity

12.17. Conjoint Support vs Conjoint Choice



Appendix Figure 5 - Conjoint support vs conjoint choice

12.18. Average Marginal Component Effect with covariates

Appendix Table 13 - Average Marginal Component Effect Wave 1

	(1) Pooled regression	(2) Country Fixed Effects	(3) All Controls	(4) Country Fixed Effects + Controls
Schedule				
Clinic schedules	-0.058***	-0.058***	-0.056***	-0.056***
	(0.003)	(0.003)	(0.004)	(0.003)
Clinic discusses then schedules	-0.047***	-0.047***	-0.047***	-0.047***
	(0.003)	(0.003)	(0.004)	(0.004)
Reminders				
Automatic Reminders	0.115***	0.115***	0.115***	0.115***
	(0.003)	(0.003)	(0.004)	(0.004)
Clinic discusses then automatic reminders	0.089***	0.089***	0.087***	0.087***
	(0.003)	(0.003)	(0.004)	(0.004)
Mandates	0.005*	0.005*	0.020***	0.020***
	(0.003)	(0.003)	(0.004)	(0.004)
Fines	-0.087***	-0.087***	-0.070***	-0.070***
	(0.003)	(0.003)	(0.004)	(0.004)
Constant	0.502***	0.501***	0.471***	0.473***
	(0.004)	(0.004)	(0.009)	(0.009)
N	143,938	143,938	95,349	95,349
R Squared	0.020	0.020	0.018	0.018

Note. Standard errors in paratheses and clustered by respondent id. Baselines: self-scheduling, no reminders, No Fines, No Mandates, Control variables: Gender (binary), Age categories, Higher education (binary), Employment Status, Parenthood, Urbanity of home town, Religiosity, Political Affiliation (left-right scale), Strength of Party Identification, Government Trust, Previous COVID Infection, Previous COVID Infection in Family, Vaccine Trust, Vaccination Status, Booster status, COVID caution, Risk Perception, Community vs Individual Prioritisation, Willingness to trade Lives over Liberty, COVID News Source, and COVID News Consumption Frequency, *p<0.1, **p<0.05, ***p<0.01

Appendix Table 14 - Average Marginal Component Effect Wave 2

	(1) Pooled regression	(2) Country Fixed Effects	(3) All Controls	(4) Country Fixed Effects + Controls
Schedule	0.043***	0.058***	0.061***	0.078***
	(0.004)	(0.005)	(0.006)	(0.007)
Reminders	0.062***	0.077***	0.063***	0.080***
	(0.004)	(0.005)	(0.007)	(0.007)
Campaign	0.041***	0.056***	0.047***	0.064***
	(0.004)	(0.005)	(0.007)	(0.007)
Mandates	-0.001	0.014***	-0.002	0.014*
	(0.005)	(0.005)	(0.007)	(0.007)
Fines	-0.111***	-0.097***	-0.099***	-0.083***
	(0.005)	(0.005)	(0.007)	(0.007)
Constant	0.493***	0.455***	0.498***	0.434***
	(0.001)	(0.004)	(0.004)	(0.004)
N	106,082	106,082	48,204	48,204
R Squared	0.008	0.009	0.009	0.009

Note. Standard errors in paratheses and clustered by respondent id. Baselines: self-scheduling, no reminders, No Fines, No Mandates, Control variables: Gender (binary), Age categories, Higher education (binary), Employment Status, Parenthood, Urbanity of home town, Religiosity, Political Affiliation (left-right scale), Strength of Party Identification, Government Trust, Previous COVID Infection, Previous COVID Infection in Family, Vaccine Trust, Vaccination Status, Booster status, COVID caution, Risk Perception, Community vs Individual Prioritisation, Willingness to trade Lives over Liberty, COVID News Source, and COVID News Consumption Frequency, *p<0.1, **p<0.05, ***p<0.01

12.19. Lexicographic Preference Analysis

Appendix Table 15 - Lexicographic preference Wave 1

	Attribute Levels	Probability of Apperance	Always choose (%)	N
Scheduling	3 levels	~33% each		
Self-schedule			25.4	6,152
Clinic schedules			19.2	4,464
Clinic discusses then schedules			20.2	4,888
Any scheduling preference			59.1	14,319
Reminders	3 levels	~33% each		
No reminders			15.9	3,854
Automatic reminders			25.8	6,248
Clinic discusses then reminders			23.1	5,596
Any reminder preference			59.1	14,302
Mandates	2 levels	50% each		
No mandates			12.5	3,021
Fines	2 levels	50% each		
No fines			17.2	4,170

Appendix Table 16 - Lexicographic preference Wave 2

	Attribute Levels	**Probability of Apperance**	**Always choose (%)**	**N**
Call to offer to schedule	2 levels	50% each	5.9	1,066
Automatic Reminders	2 levels	50% each	6.2	1,121
Social Norms	2 levels	50% each	5.6	1,005
Mandates	2 levels	50% each	4.5	800
Fines	2 levels	50% each	6.8	1,223