UNDERSTANDING DECISIONS TO ENGAGE IN PUBLIC HEALTH MEASURES DURING COVID-19

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Abstract

Widespread compliance with public health measures (PHMs) has been critical to containing the COVID-19 pandemic as well as other infectious diseases. Vaccination, mask-wearing, handwashing, and physical distancing have been among most recommended PHMs for mitigating the impacts of the pandemic. To facilitate development of public health policies and campaigns to encourage compliance with PHMs, it is necessary to gain insight into factors contributing to decisions to engage in the PHMs. The four studies presented in this dissertation are focused on investigating contributions of well-established cognitive biases, delay discounting and intolerance of uncertainty, to individual's compliance with PHMs during the COVID-19 pandemic. Approximately 7,000 participants from 13 countries were recruited for an online survey between June and August 2021. Participants completed measures of delay discounting, intolerance of uncertainty, demographics, distress level, and PHM compliance. After controlling for demographic and distress variables, delay discounting (tendency to prefer smaller immediate rewards over larger later rewards) was a negative predictor of vaccination, but a positive predictor of physical distancing and handwashing. The participants were invited to complete a follow-up study between July and August 2022 and respond to questions about engagement in protective behaviors, including vaccination status and willingness to receive a booster dose. In the sub-sample of participants who reported receiving at least one main dose of the vaccine (n = 2,547), a greater tendency to discount future rewards was associated with reduced willingness to receive a booster dose, after controlling for demographic and distress variables. In the sub-sample of participants who reported no intention to get vaccinated in 2021 (n = 251), an age x intolerance of uncertainty interaction predicted the likelihood of change in vaccination status a year later. Younger participants were more likely to change their mind about vaccination compared to older participants, especially if they were high on intolerance of uncertainty. The results of the four studies advance our understanding of health-related decision-making, offering insights into vaccine hesitancy, compliance with PHMs, and the cognitive processes associated with these choices during a pandemic. The implications extend to theoretical models, public health strategies, and interventions aimed at promoting widespread engagement in PHMs.

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Chapter 1: General Introduction

COVID-19 and its variants have had debilitating consequences on human life—both direct and indirect—that are likely to reverberate well beyond the current pandemic. Vaccination, mask-wearing, handwashing, and physical distancing are among the most recommended public health measures (PHMs) designed to mitigate the impacts of the pandemic (World Health Organization, 2020). To prevent severe illness and death, alleviate hospital burden, and maintain long-term immunity against the virus, widespread public compliance with PHMs is necessary. In order to maximize uptake of these PHMs, it is important to understand factors contributing to one's decision to engage in the protective behaviors. Recent research has largely been focused on explaining decisions to engage in PHMs using the framework of expectancy-value theories (e.g., Limbu et al., 2022; Ohnmacht et al., 2022; Wollast et al., 2021). These theories emphasize rational decision-making, namely, assessing risks and benefits of the consequences of a decision (Broomell & Chapman, 2021; Reyna et al., 2021). However, expectancy-value theories have been criticized for their lack of emphasis on cognitive biases and emotions, which both may influence decision-making (Broomell & Chapman, 2021; Reyna et al., 2021). In reality, human decision-making is a complex process driven by many variables, including demographics (e.g., age, level of education, income; Klein, 1999; Lockenhoff, 2018; Ruggeri et al., 2022), psychological factors (e.g., depression, anxiety; Hartley & Phelps, 2012; Leykin et al., 2011), and cognitive biases (e.g., Kahneman & Tversky, 1979). This dissertation aims to account for cognitive biases, together with demographic variables, to study their influence on decisions to engage in different types of PHMs.

A well-established cognitive bias in decision-making—currently ignored by expectancy-value theories— is discounting of delayed rewards. This refers to a tendency to choose a smaller and immediate reward over a larger, later reward (Green & Myerson, 2004). Delay discounting tasks are a promising behavioral measure for public health purposes. First, unlike survey approaches (frequently implemented in pandemic-related research), delay discounting tasks measure behavior (Myerson et al., 2001). Every individual has an indifference point for their subjective evaluation of immediate versus delayed rewards, the point at which the value of a future reward is sufficiently large as to offset the delay until gratification (Green & Myerson, 2004). The data for delay discounting tasks can be analyzed using the *Area under the Curve* (AuC) of the subjective values, plotted across various delay periods (Myerson et al., 2001). This measure is considered to be objective to the extent that it does not make any assumptions about theories of risk related to discounting of delayed rewards (Myerson et al., 2001).

Steep discounting of delayed rewards (i.e., choosing smaller immediate rewards over larger later rewards) is associated with many negative outcomes, including financial instability (Ruggeri et al., 2022) and problematic health behaviors (Bickel et al., 2019; Rung & Madden, 2018); both have intensified during the pandemic (Cutler & Summers, 2020; Wu et al., 2021; Zhang & Chen, 2021). This is consistent with the idea that delay discounting has been exacerbated by the conditions of the pandemic, which is another reason why this task is relevant in this context. Similarly, a tendency to choose larger later rewards has been found to predict health-related behaviors, including exercise, healthy eating, and smoking cessation (Daugherty & Brase, 2010; Robles et al., 2012). When deciding whether to engage in protective behaviors during the pandemic, an individual may consider short- and long-term costs and benefits, placing them in a position engage in delay discounting. For example, someone might weigh the immediate side effects of a vaccine versus the benefits of long-term immunity. The effect of discounting may also differ across types of protective behaviors. For example, it takes approximately 2 weeks to develop immunity to the virus after receiving the vaccine, whereas mask-wearing results in an immediate reduction of virus transmission. Another reason why delay discounting is also useful for studying the adoption of PHMs is because it can be modified. For example, cueing individuals to imagine specific future events has proven effective in reducing the degree of discounting in various populations (Rung & Madden, 2018; Mok et al., 2020; Bromberg et al., 2017; Ciaramelli et al., 2021). This raises the possibility that any detrimental courses of action driven by delay discounting could be attenuated by targeting the discounting.

Another cognitive bias not accounted for by the expectancy-value theories is intolerance of uncertainty. This refers to an inability to withstand ambiguous information, due to holding negative beliefs about uncertainty (Dugas et al., 2004). Scoring high on intolerance of uncertainty predisposes one to interpret ambiguous information as threatening (Carleton et al., 2007; Heydayati et al., 2003). Not surprisingly, this can lead to difficulties with problem-solving (Dugas et al., 1997) and decision-making (Luhmann et al., 2011). The pandemic has introduced a lot of uncertainty to everyday life, in terms of understanding how the virus is transmitted, the wellbeing and health of self and loved ones, access to vaccines, and the efficacy and potential side effects of protective measures (Baerg & Bruchmann, 2022; Del-Valle, 2022). Intolerance of uncertainty is associated with a range of emotional responses to COVID-19, including worries about contracting it (Fedorenko et al., 2021; Tull et al., 2020), spreading it (Wheaton et al., 2021), overall COVID-related stress (Paluszek et al., 2021), and physical distancing and body vigilance (Fedorenko et al., 2021). In terms of the relationship between intolerance of uncertainty and compliance with PHMs, the evidence is mixed. Some studies show no statistically significant relationship (Farias & Pilati, 2021; Millrtoh & Frey, 2021; Sauer et al., 2020), other studies show evidence of a negative relationship (Fitzgerald et al., 2022; Williams et al., 2022), and yet others show a positive relationship (Gillman et al., 2022). There is a need for more research to better understand the circumstances under which intolerance of uncertainty predicts certain types of protective behaviors. It is also possible that intolerance of uncertainty differentially predicts engagement in PHMs across various populations. For example, older adults on average have faced greater uncertainty during the pandemic (Parlapani et al., 2020). This uncertainty has also been associated with behavioral avoidance and procrastination in this population (Gosselin et al., 2022).

In considering how decision-making biases influence adoption of PHMs, it is important to distinguish between vaccination and other measures not associated with the same degree of hesitancy and refusal (e.g., Håkansson & Claesdotter, 2021). Despite the unprecedented swiftness in development, approval, and deployment of these vaccines (Ball, 2021), they are largely safe and effective (Stuart et al., 2022). However, the emergence of new variants and the need for additional doses may contribute to vaccine hesitancy. This is despite the fact that the vaccines are effective even in the face of novel variants (Goel et al., 2021; Munro et al., 2021), and that waning immunity can be addressed by booster doses (Accorsi et al., 2022; Barda et al., 2021; Grewal et al., 2022). It is important to investigate people's deliberation process in deciding to get vaccinated to inform public health policies and campaigns that would be most effective in encouraging vaccination.

When rapid mobilization of interventions is necessary (e.g., during a pandemic), those that bypass risk perception and cognition (e.g., lockdowns and travel restrictions) appear most effective in eliciting short-term behavior changes (Brewer et al., 2018; Broomell & Chapman, 2021). However, when long-term maintenance of PHM adoption is desired (e.g., getting a flu shot every season), effective interventions must be intrinsically motivated, and thus must incorporate thoughts and feelings (e.g., risk beliefs) and social processes (e.g., social norms, altruism). Effective interventions must also recognize that changing related attitudes and behaviours involves deliberation and consideration of personally relevant factors (Prochaska & Velicer, 1997). Successful interventions meet the person where they are, motivating further consideration, and encouraging movement towards the desired behavior (Miller & Rollnick, 2013; Morton et al., 2015). Chapter 4 is focused on individuals who received at least one dose of the vaccine. It is particularly important to understand the process of change in people's attitudes towards vaccines and boosters as the protective behaviors become increasingly more optional and responsibility for long-term immunity maintenance shifts from official mandates to individual decision-making. Doing so requires an in-depth examination of how cognitive biases influence changes in decisions and attitudes toward PHMs over time. From a public health perspective, it is crucial to recognize that one size does not fit all in the realm of health behavior change. Different individuals find themselves at varying stages of readiness for change, necessitating a tailored approach to intervention strategies. Therefore, Chapter 5 is focused on investigating individuals who originally refused to get vaccinated and exploring predictors of changing their mind a year later.

The clear need for broad and sustained vaccine uptake drives the initiative to identify and promote ways to increase vaccination rates. Methods to induce behavioral change, including public education campaigns, reminders, attention to societal impact, and monetary incentives, all have shown some success (Szilagyi et al., 2021; Ball, 2021; Dai et al., 2021). However, to address ongoing and future vaccine hesitancy associated with COVID-19 and other infectious diseases, there is a need to develop solutions that target unique challenges facing various populations and produce reliable longer-term behavioral change. Special attention should be given to challenges facing populations that are considered at high-risk of COVID-19 exposure and infection (e.g., older adults, essential workers) to provide more uniquely tailored interventions to these groups. Given that vaccine immunity wanes faster over time among older adults (Hägg & Religa, 2022), it is necessary to address challenges with vaccine deployment in that population. Vaccine hesitancy and concerns about immediate side effects have been identified among the main challenges with vaccine uptake in older adults (Gaitán-Rossi et al., 2022; Liang et al., 2022; Zhang et al., 2022). Although there is little evidence for risk compensation in the general population (e.g., increased mask-wearing or physical distancing in the unvaccinated) (Goldszmidt et al., 2021), it is possible that it occurs more systematically among older adults given the increased actual and perceived risk in that population. Further, older adults tend to be more resistant (Ferrini et al., 1994) and less encouraged (Tucker et al., 2004) to change their health-related behaviours. Therefore, encouragement to engage in PHMs may require additional considerations in this population.

The four studies described in this dissertation investigate contributions of cognitive biases, discounting of delayed rewards and intolerance of uncertainty, to protective behaviors (vaccination and other PHMs), after controlling for demographic variables (i.e., age, essential worker status, level of education, and income) that have been previously found to be significant predictors of PHM compliance (e.g., Papageorge et al., 2021; Pasion et al., 2020; Xu et al., 2022). This dissertation is also focused on investigating long-term predictors of changing minds about vaccination among those who initially expressed no intention to get vaccinated, as well as predictors of willingness to receive a booster among those who received at least one dose. The four studies are based on the data collected longitudinally across two time points: June to August 2021, with the follow up in July to August 2022.

In the first study, the primary goal is to examine how delay discounting relates to vaccination status among individuals recruited in June and July 2021. In Study 2, the goal is to reproduce these results in a larger sample recruited between June and August 2021. In Study 2, the scope is extended to investigate the role of delay discounting in predicting other protective behaviors, including physical distancing, hygiene practices, and mask-wearing. In Study 3, the focus is on intolerance of uncertainty and age as predictors of changing minds about vaccination among individuals who expressed no intention of getting vaccinated. Lastly, Study 4 focuses on delay discounting as a predictor of willingness to receive a booster dose. Overall, the four studies reported shed light on the important role of cognitive biases in shaping individuals' engagement in protective health behaviors. Additionally, this research contributes to our understanding of the long-term predictors of changes in vaccination decisions, enhancing our insights into the dynamic process of health-related decision-making.

Chapter 2: Short-Sighted Decision-Making by Those Not Vaccinated Against COVID-19

Julia G. Halilova[1], Samuel Fynes-Clinton[2], Leonard Green[3], Joel Myerson[3], Jianhong Wu[1], Kai Ruggeri[4], Donna Rose Addis[2,5,6*], R. Shayna Rosenbaum[1,2*]

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COVID-19 and its variants have had debilitating consequences to human life—both direct and indirect—that are likely to reverberate well beyond the current pandemic. To prevent severe illness and death, and alleviate hospital burden, extreme mitigation measures have been imposed, including lockdowns, quarantines, physical distancing, mask-wearing, and, more recently, the rapid, wide-scale deployment of safe and effective vaccines for SARS-CoV-2. Maximizing vaccine uptake is essential for containing the COVID-19 pandemic (Lopez Bernal et al., 2021) as well as other infectious diseases (World Health Organization, n.d.), but it is threatened by vaccine hesitancy and resistance (Campos-Mercade et al., 2021; Szilagyi et al., 2021). It is not enough to rely on predictive modeling of COVID-19 spread and vaccine uptake to guide behavioral change (Campos-Mercade et al., 2021). Identifying predictors of vaccine hesitancy and unwillingness is crucial to reduce the severity and spread of COVID-19 (van Bavel et al., 2020), particularly given continued emergence of variants. Greater insight into the processes involved in vaccination choices can lead to strategies to better align behavior with medical and public health recommendations (Sinclair et al., 2021).

Mounting evidence shows that, despite the unprecedented swiftness in development, approval, and deployment (Ball, 2021), COVID-19 vaccines are largely safe and effective in protecting individuals from serious illness (Stuart et al., 2022). Their effectiveness has been shown even in the face of novel variants (Goel et al., 2021; Munro et al., 2021), and that waning immunity can be addressed by an additional (booster) dose (Barda et al., 2021; Accorsi et al., 2022). The UN's global call to distribute primary doses widely and equitably attests to the international acceptance of COVID-19 vaccines (WHO, 2021). Nevertheless, both the need for additional doses and the emergence of variants of concern that are less responsive to existing vaccines pose threats to vaccine acceptance. Future uncertainties surrounding vaccination strategy may further intensify 'anti-vax' attitudes (Goldberg, 2021). The picture is complicated by demographic variables that can influence vaccine status: Older age, advanced education, and higher income increase the likelihood of vaccine access and the likelihood that they will choose to be vaccinated (Aw et al., 2021; Kerr et al., 2021). Likewise, factors amplifying actual or perceived risk of exposure and infection, including living in geographic locales with higher case/death rates and working on the frontline, may propel individuals to seek vaccination (Karlsson et al., 2021; Lin et al., 2021).

The clear and present need for broad and sustained vaccine uptake to end the COVID-19 pandemic and prevent future outbreaks has fueled scientists' and public health officials' drive to identify and promote ways to increase vaccination rates. Methods to induce behavioral change, including public education campaigns, reminders, attention to societal impact, and monetary incentives, have all had some success (Dai et al., 2021), at least in the short term. To address ongoing and future challenges associated with COVID-19 and other disease threats, there is an urgent need for solutions that produce longer-term behavioral change with respect to vaccination unwillingness and hesitancy. The first step is to identify target cognitive biases that predict vaccination decisions.

A promising behavioral economic measure of decision-making is delay discounting, which assesses the tendency to forgo larger, delayed rewards in favor of smaller, immediate rewards. Each individual has an indifference point where the value of a future reward is sufficiently large as to offset the delay until gratification (Green & Myerson, 2004). The higher the indifference point, the more an individual is taking future benefits into account and the greater the subjective value of the delayed reward. The lower the indifference point, the lower the subjective value and the greater the short-sighted bias in decision-making. Steep discounting of delayed rewards (evidenced by lower indifference points) is associated with many negative outcomes, including financial instability (Ruggeri et al., 2021) and problematic health behaviors (Bickel et al., 2019; Rung & Madden, 2018), both of which have intensified since the start of the pandemic (Cutler & Summers, 2020; Wu et al., 2021; Zhang & Chen, 2021). Critically, for public health purposes, delay discounting is modifiable. For example, cueing individuals to imagine specific future events reduces the degree of discounting in diverse populations (Mok et al., 2020; Bromberg et al., 2017; Ciaramelli et al., 2021).

Here, we combine a large, multi-nation sample with a highly sensitive online delay discounting task, using an adjusting-amount procedure to determine an individual's short-sighted bias in decision-making. We strategically sampled from a range of industrialized nations across Australasia, Europe, and North America that varied in local severity of the pandemic due to variants of concern at the time of testing (June 27 to July 16, 2021; van Bavel et al., 2020). This was confirmed across the 13 nations we sampled by examining real-time pandemic severity statistics linked to participation dates (see Figure 1A). Data collection took place after primary vaccines were deployed and before booster doses were introduced. Average rates of vaccination (partial and full, combined) ranged from 15% to 69% across nations during our testing window (Figure 1B). Our key analyses demonstrate that short-sighted decision-making emerges as a unique predictor of being unvaccinated, even after accounting for country-level differences as well as demographics and mental health variables. Delay-discounting therefore holds promise as a predictor of vaccine unwillingness and as a target for interventions.

Method

Participants

Using Prolific's built-in inclusion/exclusion function, the study was available only to users meeting the following inclusion criteria: aged 18 years or older, fluent in English, currently residing in one of 14 target countries across North America, Europe, Australasia, and Africa, and free from neurological impairments or learning disabilities. All 5,193 participants provided informed consent and received monetary compensation at a rate recommended by Prolific. Data from 320 individuals were excluded from the analyses: 17 due to failure to meet inclusion criteria (e.g., residing in a non-targeted country); 176 due to non-completion of the survey; 86 due to not reporting vaccination status; and 41 due to responding incorrectly to more than one attention check item (see below). Data from 421 participants from South Africa also were excluded due to challenges in obtaining reliable COVID-related metrics at the population level (e.g., COVID-19 case rates, vaccination rate), substantial differences in government response compared to other countries included (Abdool Karim, 2020), and a very low vaccination rate (only 23 participants from South Africa in our sample reported being vaccinated). The study was approved by the York University and Baycrest Research Ethics Boards for research with human participants (REB #08-57), and all research was conducted in accordance with the Declaration of Helsinki.

Materials

All data were collected in an online Qualtrics survey environment. Participants completed a survey that included the following sections (along with other measures not reported here):

Delay Discounting Task

In this intertemporal choice procedure (Mok et al., 2020; Ciaramelli et al., 2021), participants viewed pairs of monetary amounts and were asked to choose between a smaller, immediate reward, which varied between trials, and a larger, delayed reward of $2,000. Participants were asked to make six choices at each of seven delays (waiting 1 week, 1 month, 3 months, 6 months, 1 year, 3 years, and 10 years before receiving the $2000 reward). An iterative, adjusting-amount procedure was used in which the amount of the immediate reward was increased or decreased based on the participant's previous choice at that delay, converging on the amount of the immediate reward equivalent in subjective value to the delayed reward. The first adjustment was half of the difference between the immediate and delayed amounts presented on the first trial, with each subsequent adjustment being half of the preceding adjustment. For example, in the condition where a future reward of $2000 could be received in 3 years, the first choice presented to the participants would be "$1000 right now or $2000 in 3 years." If the participant chose "$2000 in 3 years," the choice on the second trial would be "$1500 right now" or "$2000 in 3 years." If the participant then chose "$1500 right now", the choice on the third trial would be "$1250 right now or $2000 in 3 years." Following the sixth and final trial of each condition, the subjective value of the delayed reward was estimated as the amount of the immediate reward that would be presented on a seventh trial. Degree of discounting was measured by examining the relation of subjective value to delay of reward and computing AuC, a single, theoretically neutral measure of discounting (Myerson et al., 2001).

Demographic Questionnaire

Participants completed a demographics questionnaire that included items probing: country of residence, age, gender (female/male/non-binary), highest level of education obtained (secondary schooling/undergraduate degree or professional equivalent/postgraduate degree), and essential occupation (yes/no). Occupations deemed essential during the pandemic are those supplying critical services: government; health and safety (e.g., healthcare, emergency response); utilities (e.g., water, energy, sanitation, transport, communications); food (e.g., supermarkets); and manufacturing. A measure of relative income was used: participants estimated their current income on a sliding scale (0-100) marked by points representing low (0), average (50), and high (100) incomes in their own country/region (Adler et al., 2000).

Mental Health Questionnaires

Presence and severity of anxiety and depressive symptoms was assessed by the Generalized Anxiety Disorder 7-item (GAD-7) scale (Spitzer et al., 2006); and the Patient Health Questionnaire 9-item (PHQ-9) scale (Kroenke & Spitzer, 2002). Both scales have been widely used and demonstrated good psychometric properties in clinical and non-clinical samples (e.g., Bianchi et al., 2022; Johnson et al., 2019; Merino-Soto et al., 2023; Sun et al., 2020). Participants rated the frequency of symptoms experienced over the past two weeks on a four-point scale (0 = not at all; 3 = nearly every day). Internal consistency of responses on both scales was assessed using function *alpha()*[1] of the R package *psych* (Revelle, 2021). The scales achieved very good internal consistency with $\alpha = 0.88$ and $\alpha = 0.92$ for PHQ-9 and GAD-7, respectively. For each scale, a total score was computed, where higher scores reflect more severe symptoms. Total scores from these measures were standardized and then summed to create a psychological distress index.

Attention Checks

Three items from the Conscientious Responder Scale (Marjanovic et al., 2015) were included at select points within the survey to identify random responders (e.g., “To answer this question, please choose option three, neither agree nor disagree.").

Analyses

Regional COVID-19 Severity Index

Weekly cases/deaths, cumulative total cases/deaths, and cumulative cases/deaths per 100,000 people were extracted from the ECDC COVID-19 statistics (Mathieu et al., 2021) for each participant on the week of survey completion for the country in which they resided. The dimensionality of these data was reduced using principal components analysis (PCA) with the aim of isolating a single component reflecting shared variance across the different COVID-19 severity statistics. PCA is a multivariate technique used to reduce data dimensionality whilst maximally maintaining its variability. In the present study, PCA was conducted in R using the *prcomp()* function of the *stats* package and results were extracted using the package *factoextra* (Kassambara & Mundt, 2020). The data were first mean-centered and scaled (i.e., mean = 0, standard deviation = 1), rendering the analysis equivalent to running PCA on the correlation matrix. The *prcomp()* function PCA is performed using the singular value decomposition method and results in orthogonal principal components (PC) that maximally retain the correlations among individuals. PCs with an eigenvalue (λ) >1 were considered reliable. The Regional COVID-19 Severity Index comprised the component scores from PC1, which accounted for 63.5% of variance in the data and corresponded to shared variance across all ECDC variables ($\lambda = 3.81$). Higher individual component scores reflected greater regional severity of COVID-19.

[1] Given unidimensionality of both scales, alpha was determined to be an appropriate measure of internal consistency.

Multilevel Logistic Model

This model was constructed using R packages *lme4* (Bates et al., 2012) and *lmerTest* (Kuznetsova et al., 2017), with the outcome variable (participants' vaccination status; Level 1) nested within country (Level 2), and with age, education level, income, essential worker status, psychological distress index, and AuC as predictors. The model was estimated using maximum likelihood with Laplace approximation.

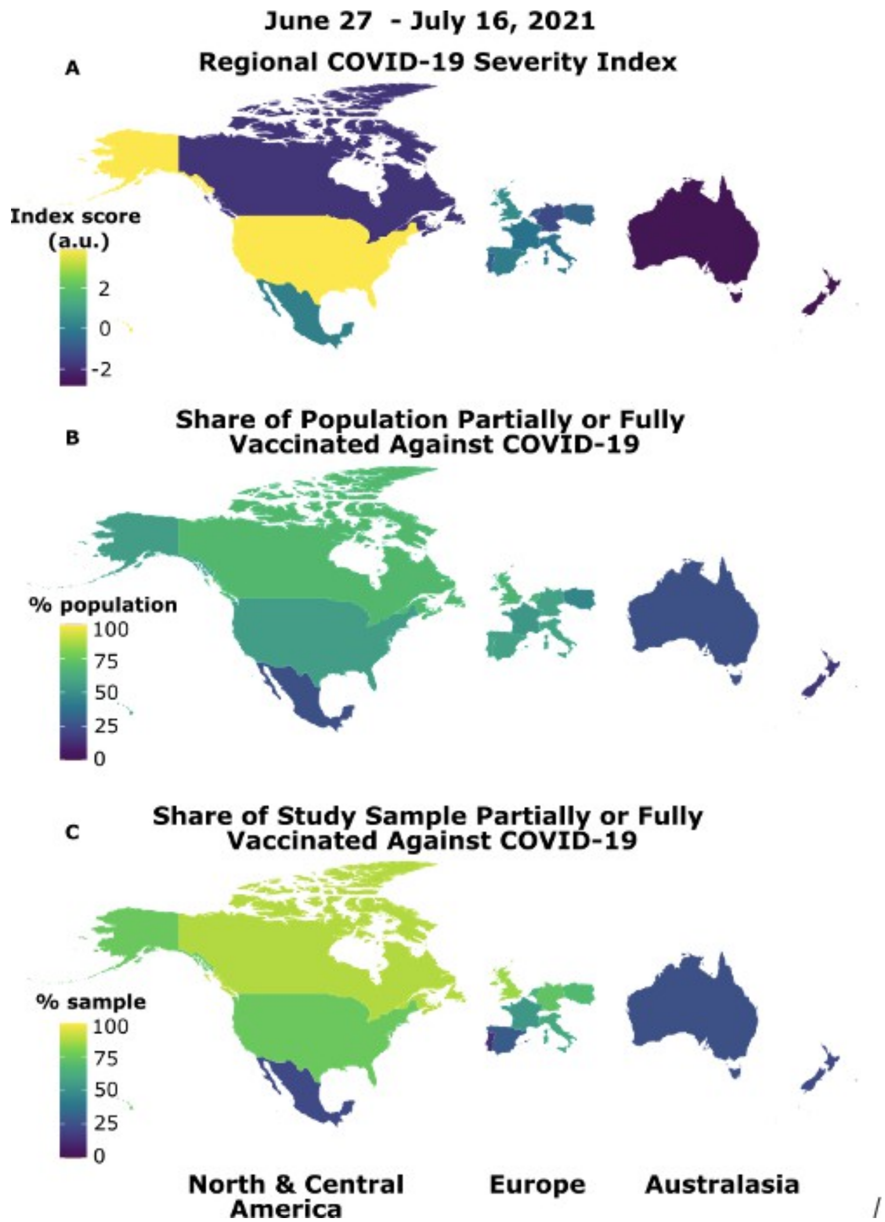
Data Visualization

Plots were constructed using R package *ggplot2* (Wickham, 2016). Geomapping of the Regional COVID-19 Severity Index and vaccination rates was achieved using the *R* package *maps* (Becker & Wilks, 2021).

Results

Recruitment was conducted through an online platform (Prolific.co) from June 27, 2021 to July 16, 2021. Data from 4,452 participants were analyzed: 1,566 were fully vaccinated (two doses or one dose for J&J/Jansen), 1,033 were partially vaccinated (e.g., one dose for Moderna/Pfizer); 1,440 were unvaccinated but planning to be, and 413 were unvaccinated and not planning to be. The groups were combined into a binary vaccination status variable (i.e., vaccinated vs. unvaccinated) to capture participants' vaccination decisions. Figure 2.1C shows the proportion of our sample from each country who were vaccinated.

Figure 2.1 Pandemic and Vaccine Situation Across Our Sample at the Time of Testing



Note. The R package "maps" was used to visualize regional differences on the COVID-19 Regional Severity Index and population and study sample vaccine situations (https://cran.r-project.org/web/packages/maps/index.html). (A) The Regional COVID-19 Severity Index is a nation's component score (in arbitrary units, a.u.) from a principal component analysis of weekly COVID-19 cases/death rates; total cases/deaths since the first week of 2020, and population-adjusted total cases/deaths per 100,000. These nation-specific data were extracted from the European Centre for Disease Prevention and Control COVID-19 statistics (European Centre for Disease Prevention and Control, 2021) for each participant based on the week they completed the study. (B) The share of each nation's population who were partially or fully vaccinated (i.e., one or more doses) against COVID-19, shown as the average percentage across our testing window; data were extracted from Mathieu et al., 2020. These data show lower proportions (15%) in countries only beginning vaccine roll-out (e.g., New Zealand) to almost 70% of the population in countries with earlier access to vaccines (e.g., United Kingdom, United States) and/or rapid uptake (e.g., Canada). (C) The share of participants from each country who were partially or fully vaccinated against COVID-19 (range 13% to 88%). Our sample was generally representative of population rates; the difference between sample rates (C) and population rates (B) for each country are plotted in Figure 1.

Participants indicated their gender, age, highest level of education, and whether they worked in an occupation deemed essential during the pandemic. Given the multinational sample, income was assessed as participants' rating of their income as low, average, and high incomes in their own region/country on a 100-point scale (Adler et al., 2000). A psychological distress index was included to control for anxiety and depressive symptoms that may interact with other variables, including delay discounting (Bickel et al., 2019), in the analysis. Delay discounting was measured using an established intertemporal choice procedure (Ciaramelli et al., 2021; Mok et al., 2020). On each of 42 trials, participants decided between a larger, later hypothetical reward (e.g., $2,000 one month from now) and a smaller, immediate reward (e.g., $1,000 today). A staircase procedure adaptively determined the choice amounts presented on each trial based on prior responding. Given the existence of multiple discounting models (Green & Myerson, 2004), a well-established, theoretically neutral measure, Area-Under-the-Curve (AuC), was used to assess biased decision-making (Myerson et al., 2001). Descriptive statistics for all key predictors in our analyses (as well as gender) are presented in Table 2.1 by vaccination status.

Table 2.1 Participants Characteristics by Vaccination Status

	unvaccinated (n = 1853)	**vaccinated** (n = 2599)
Gender (% female/male/non-binary)	45/53/1	53/46/1
Mean age in years (SD)	27.96 (8.79)	32.22 (11.48)
Highest level of education (% secondary/undergraduate/postgraduate)	32/52/16	28/50/22
Mean rating of relative income* (SD)	36.31 (23.8)	40.39 (23.97)
Essential worker (% yes)	15	27
Mean psychological distress index score (SD)	0.11 (1.89)	-0.08 (1.89)
Delay discounting (AuC)	0.38 (0.25)	0.41 (0.25)

Note. *100-point scale, where 0 = low, 50 = medium, and 100 = high relative to others in the participants' country/region. AuC = Area-under-the-Curve (range, 0-1); undergrad = undergraduate degree or professional equivalent; postgrad = postgraduate degree (e.g., Masters, PhD); SD = standard deviation.

Our key analysis determined the unique contribution of discounting delayed rewards to predicting the odds of being vaccinated after accounting for other variables. First, a multilevel logistic model was constructed with vaccination status (unvaccinated vs. vaccinated) as the outcome variable and AuC as the only predictor in the model. To account for possible systematic differences across countries (e.g., COVID-related severity, population vaccination rates, government response), each participant's vaccination status (Level 1) was nested within country (Level 2; intraclass correlation, *ICC* = 0.30). AuC was positively associated with the likelihood of being vaccinated, OR = 1.76, 95% CI [1.32, 2.33]. The model was then expanded to test for the effect of AuC on vaccination status, after controlling for age, education level, income, essential workers status, and psychological distress. The model accounted for significantly more variance in the data compared to an unconditional intercept-only model, $\chi^2(6) = 221.54$, $p < .001$. Results show that the tendency to choose larger future rewards over smaller immediate ones increases the odds of being vaccinated above and beyond the influence of other variables in the model (*OR* = 1.70; 95% CI [1.27, 2.28]; Table 2.2). All of these variables were positively associated with the likelihood of being vaccinated, with the increase in odds of being vaccinated ranging from 1.00, 95% CI [0.96, 1.04] for psychological distress to 1.79, 95% CI [1.48, 2.17] for essential worker status (Table 2.2).

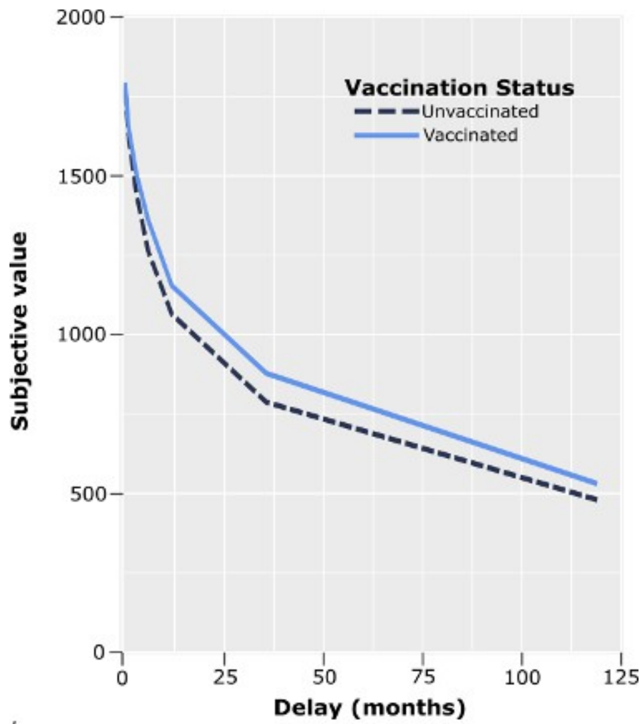
Table 2.2 Results of Multilevel Model Predicting Vaccination Status

Fixed Effects	Estimate	SE	*z*	*p*	OR	95% CI
Intercept	-2.50	0.42	-5.98	< .001	0.08	[0.04, 0.19]
Age	0.04	0.01	8.56	< .001	1.04	[1.02, 1.04]
Education level	0.27	0.06	4.89	< .001	1.31	[1.18, 1.46]
Income	0.004	0.002	2.66	.008	1.00	[1.00, 1.01]
Essential worker	0.58	0.10	5.94	< .001	1.79	[1.48, 2.17]
Psychological distress	0.001	0.02	0.02	0.98	1.00	[0.96, 1.04]
Delay discounting (AuC)	0.53	0.15	3.56	< .001	1.70	[1.27, 2.28]
Random Effects	Estimate	SD				

Intercept error variance (country)	1.54	1.24

Note. AuC = Area-under-the-Curve; CI = Confidence Interval; OR = Odds ratio; SD = Standard deviation; SE = Standard error

Figure 2.2 Discounting Curve in Vaccinated and Unvaccinated Participants



Note. Subjective value (mean indifference point) of the $2,000 delayed reward as a function of the delay to its receipt. Area-under-the-Curve (AuC) was used as a measure of delay discounting. Unvaccinated individuals on average tended to discount future rewards more steeply (i.e., have smaller AuCs) than vaccinated individuals.

Discussion

We show that COVID-19 vaccination is predicted by a greater propensity to choose larger, future rewards over smaller, immediate rewards, as indicated by shallower delay discounting (Figure 2.2). This finding emerges across multiple countries that varied in pandemic severity and vaccination rates at the time of testing. Discounting explains unique variance over and above other predictors of vaccine acceptance, including higher age, education level, and income level, as well as employment as an essential worker. Lack of protection against COVID-19 places individuals and societies at sustained risk of illness and death, prolonging a safe return to pre-pandemic life. Identifying delay discounting as a source of vaccine non-compliance provides an avenue for inducing positive behavioral change in the face of global threats to health and safety (Wismans et al., 2021).

The current results are in line with previous findings showing that steeper delay discounting is a key predictor of numerous health-related issues, including obesity, addictive behaviors, and anxiety and mood disorders (Bromberg et al., 2017; Ciaramelli et al., 2021; Rung & Madden, 2018), many of which are exacerbated by pandemic conditions (Wu et al., 2021; Zhang & Chen, 2021). The extent to which delay discounting is a predictor of compliance with pandemic-mitigating behaviors other than vaccination (e.g., physical distancing, mask-wearing) is less clear (Lo Presti et al., 2022; Strickland et al., 2022; Wismans et al., 2021). Seemingly weak or contradictory findings may reflect the influence of confounding factors, such as psychological distress, which tends to be positively related to delay discounting (DeAngelis et al., 2021). Given the association between psychological distress and delay discounting (Myerson et al., 2001), it is perhaps not surprising that psychological distress did not predict vaccination status after controlling for other variables.

Although our multi-national sample spanned three global regions, it was nevertheless limited to industrialized countries that, with the exception of Mexico, fall under the Western Educated Industrialized Rich and Democratic (WEIRD) designation (Henrich et al., 2010). As vaccine availability becomes more widespread globally, this work should be expanded to determine the utility of delay discounting as a predictor of vaccine acceptance in non-industrialized countries, particularly given the considerably different government responses, vaccine access, and/or economic situations. We recognize that in addition to the factors examined here, vaccination decisions are also influenced by individual differences in political ideology, respect for authority, vaccine literacy, trust in government public health agencies, and trust in science more generally (Munro et al., 2021). In contrast to these factors, which can be challenging to measure, discounting is a simple, well-established behavioral economic construct that the present findings show is a conspicuous indicator of vaccination choices.

Discounting the value of future monetary rewards parallels opting for the smaller, immediate benefits of not getting vaccinated (e.g., avoiding initial side effects) versus the longer-term benefits of vaccination (e.g., immunity to COVID-19, increased social interactions). That is, steep discounting is a proxy for short-sighted decision-making. Sustainable policy applications to encourage vaccine uptake should directly address short-sighted decision-making in the form of steep discounting through use of established methods that make future consequences more salient (Bromberg et al., 2017; Mok et al., 2020; Rung & Madden, 2018; Sinclair et al., 2021). This approach can be supplemented by immediate, modest monetary incentives, which have shown some success encouraging PHM adoption on their own (Dai et al., 2021). Such interventions are critical in preparation for encouraging vaccination against newly emerging COVID-19 variants and other infectious diseases. Turning to the behavioral sciences to understand the decision-making process underlying vaccine acceptance is crucial when the outcome of the decision has the potential to harm oneself and other people.

In this chapter, we investigated delay discounting as a predictor of vaccine hesitancy in individuals recruited in June and July 2021. The data presented here were analysed and submitted for publication while the data collection continued until August 2021. Under the circumstances of the global health crisis, there was a compelling need for COVID-19-related studies and data to be disseminated and shared promptly. This was not only essential for advancing the scientific understanding of the COVID-19 impact, but also for informing evidence-based public policies crucial for minimizing its spread and safeguarding public health. Therefore, we decided to submit our findings for publication before data collection was finished. By doing so, we aimed to expedite the availability of our research insights to the scientific community, policymakers, and the public at large.

In Chapter 3, one goal is to reproduce the results of Chapter 2 in a larger sample, using all the data collected between June and August 2021 (including the partial data reported in Chapter 2). Another goal is to investigate delay discounting as predictor of engaging in other protective behaviors, including physical distancing, cleaning, and mask-wearing. This is an important first step toward understanding whether public health policies and public messaging should take a similar approach across various protective behaviors, or if a more nuanced and tailored approach is required.

Chapter 3: Delay Discounting Differentially Predicts Decisions to Engage in Various Protective Behaviors

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Widespread compliance with PHMs has been critical to containing the COVID-19 pandemic as well as other infectious diseases. Vaccination, mask-wearing, handwashing, and physical distancing are among the most commonly recommended PHMs, designed to mitigate the impact of the pandemic (World Health Organization, 2020). Widespread public compliance with PHMs is necessary to prevent severe illness and death, and alleviate hospital burden, and is of increasing importance in light of the global population aging. Understanding decisions to engage in protective behaviors during COVID-19 will help inform ways to encourage PHM compliance, with important implications for managing future pandemics.

Here we demonstrate the value of a well-established cognitive bias in decision-making as a predictor of adherence to different PHMs during the pandemic. Discounting of delayed rewards, where the value of rewards decreases as a function of delay (Green & Myerson, 2004), is a cognitive bias that is associated with financial instability (Ruggeri et al., 2022) and problematic health behaviors (e.g., Barlow et al., 2016; Bickel et al., 2019; Daugherty & Brase, 2010; Robles et al., 2011; Rung & Madden, 2018), including behaviors that were heightened during the COVID-19 pandemic (Cutler & Summers, 2020; Halilova et al., 2022; Wu et al., 2021; Zhang & Chen, 2021). There are several reasons why delay discounting is a promising measure for public health purposes, one that may be leveraged to address health crises on a global scale. Unlike survey approaches that have been frequently implemented in pandemic-related research and that are subject to misreporting (Ruggeri et al., 2023), delay discounting can be measured in a less conspicuous and more objective way (Myerson et al., 2001). The degree of delay discounting can also be reduced through cognitive interventions that engage greater future-oriented thinking, across diverse populations (Bromberg et al., 2017; Ciaramelli et al., 2021; Mok et al., 2020; Rung & Madden, 2018).

The promise of delay discounting as a predictor of compliance with COVID-19 PHMs has been recognized in recent research involving diverse populations from different countries, tested throughout the pandemic (Byrne et al., 2021; Calluso et al., 2021; DeAngeli et al., 2022; Halilova et al., 2022; Hudson et al., 2022; Krawiec et al., 2022; Lloyd et al., 2021; Strickland et al., 2022; Wismans et al., 2021). A consistent negative relationship has been found between delay discounting and vaccination attitudes and status (Halilova et al., 2022; Hudson et al., 2022; Strickland et al., 2022). Evidence for a relationship between delay discounting and other PHMs (e.g., handwashing/cleaning, physical distancing, and mask-wearing), however, is mixed, with some studies finding a negative relationship (Byrne et al., 2021; DeAngelis et al., 2022; Lloyd et al., 2021), and other studies finding a positive relationship (Calluso et al., 2021; Wismans et al., 2021). Yet other studies find no relationship between delay discounting and compliance (Krawiec et al., 2022). The picture is further complicated by impact severity (e.g., number of new daily cases or number of death related to COVID-19) and government-mandated restrictions (e.g., mandatory masks in all public places vs. recommended mask-wearing), which differed in rate and degree across countries and at the different timepoints of data collection (see Table 3.1). For example, New Zealand maintained a nearly COVID-free environment during May and June, 2020 (Mathieu et al., 2020). In such safe environment, the relationship between delay discounting PHM compliance may be relatively low, as people might not feel the need to protect themselves.

Previous research also indicates the importance of distinguishing between different protective behaviors, as some of them may be differentially affected by one's personality and demographic factors (e.g., Choi et al., 2022; MacIntyre et al., 2021), as well as economic considerations (Petherick et al., 2021). In a recent meta-analysis, the intention-behavior relationships for different PHMs (including physical distancing, hand hygiene, and mask wearing) were assessed (Liang et al., 2022). Although several studies reported a positive intention-behavior relationship when it comes to physical distancing and hand hygiene, there was a non-significant intention-behavior relationship for mask wearing (Liang et al., 2022). Overall, the literature suggests that decisions to comply with different PHMs may rely on different mechanisms and be influenced by different factors.

Figure 3.1 Studies Examining the Relationship Between Delay Discounting and PHM Compliance During the COVID-19 Pandemic

Study	PHMs studied	Measure of Discounting	*n*	Countr(ies) where data were collected	Time of data collection	Correlation of delay discounting with PHMs
Byrne et al., 2021	Physical distancing, mask-wearing	Area-under-the-Curve	404	United States	July – December 2020	Greater delay discounting associated with less physical distancing and mask wearing.
Lloyd et al., 2021	Physical distancing	Delay discounting magnitude effect slope (*m*), and its intercept (*c*)	442	United Kingdom	April – May, 2020	Greater delay discounting predicted poorer adherence to physical distancing measures.
DeAngelis et al., 2022	Physical distancing, stockpiling	Log-transformed *k* value	3,686	96 countries	March – May 2020	Discounting negatively correlated with physical distancing and positively correlated with stockpiling.
Calluso et al., 2021	Going out, hand sanitation, use of protective equipment	Log-transformed *k* value	353	Italy	May 2020	Discounting rate was positively related to compliance physical distancing and mask- and glove-wearing.
Wismans et al., 2021	Social distancing, hygiene	Log-transformed *k* value	6,759	Belgium, France, Ireland, Italy, the Netherlands, Portugal, Sweden	June 2020	Discounting rate positively related to social distancing and hygiene compliance.
Krawiec et al., 2022	Physical distancing, mask-wearing, disinfection	Log-transformed *k* value	338	Poland	December 2020 – February 2021	No significant correlation between delay discounting and any of the PHMs studied.

It is possible that when deciding whether to engage in PHMs, an individual may consider the short- and long-term costs and benefits of engaging in those behaviors (e.g., immediate side effects of a vaccine vs. long-term immunity). Importantly, the effect of delay discounting may differ across types of protective behaviors, depending on the perceived temporal delay of PHM benefits. This may help explain the mixed findings in the literature. For example, it takes approximately 2 weeks to develop immunity to the virus after receiving the vaccine, and the benefits last for months. In contrast, physically distancing from others results in an immediate reduction of virus transmission, but it is limited to that specific time (e.g., Bernal et al., 2021; Chea et al., 2021; Sun et al., 2022). The current research examined the relationship between delay discounting and compliance with different PHMs (i.e., vaccination status, handwashing/cleaning, physical distancing, and mask-wearing) in mid-2021, based on a large sample of adults from 13 countries. These countries continued to promote PHMs in the face of the ongoing COVID-19 pandemic. We predicted that greater discounting of delayed rewards (i.e., more short-sighted thinking) would be associated with a reduced likelihood of being vaccinated, but increased frequency of engaging in other PHMs that provide more immediate benefits, such as handwashing and cleaning, physical distancing, and mask-wearing. These associations were predicted to hold even after controlling for demographic variables, psychological distress, and intolerance of uncertainty. The multinational sample also allowed us to explore the relationship between the variables across 13 countries that varied in pandemic severity, vaccination rates, and government mandates.

Method

Ethics, Consent and Permissions

The research was approved by the York University and Baycrest Research Ethics Boards REB# 19-07 for research with human participants, and all research was conducted in accordance with the Declaration of Helsinki. Prior to their participation in the study, all of the participants signed a consent form, confirming their willingness to participate in the research.

Consent to Publish

All participants provided their consent for their anonymized data to be presented in scientific conferences, journal articles, and published on the open access repository, Open Science Framework.

Participants

Recruitment was conducted through an online platform (Prolific.co) from June 27, 2021 to August 31, 2021[2]. Using Prolific's built-in inclusion/exclusion filters, the study was available only to users meeting the following inclusion criteria: aged 18 years or older, fluent in English, normally residing in one of 14 target countries[3] across North America, Europe, Australasia, and Africa, and free from neurological impairments or learning disabilities. Target countries were selected with the goal of capturing varying COVID-19 impact severity and a range of government mandates in place at the time of testing (Mathieu et al., 2020). Countries with fewer than 200 active participants on the recruitment platform were not included in the target list. Of the 7,667 participants who provided informed consent, data from 320 individuals were excluded due to failure to meet inclusion criteria (e.g., currently residing in a non-targeted country); non-completion of the survey (i.e., those who completed less than 95% of the survey); and/or responding incorrectly to more than one attention check item (see below). Data from 421 participants from South Africa were excluded due to a substantially different approach in government response, limited vaccine availability, and additional obstacles to compliance with PHMs (e.g., lack of access to clean water; Staunton et al., 2020). The final data set was composed of 6,926 participants who were on average 28.62 (*sd* = 10.18) years old; 58% were female, 40% male, and 2% non-binary. Approximately 35% of the sample had achieved secondary level education, 48% had an undergraduate degree, and 16% of the sample achieved postgraduate education. Approximately 23% of the sample self-identified as essential workers. Average subjective rating of relative income among participants (on a 100-point sliding scale; Adler et al., 2000; Smith et al., 2019) was 36.31 (*sd* = 23.8).

Measures

PHMs During COVID-19

Participants were asked a series of questions about their compliance with protective behaviors during COVID-19. Participants chose between 5 options in response to the question about their vaccination status: 1 = yes, I have received all necessary doses, 2 = yes, although I require another dose, 3 = no, but I am planning to get vaccinated, 4 = no, I am not planning to get

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[2]A subset of the data (n = 5,193) collected from June 27, 2021 to July 16, 2021 was previously reported in Halilova et al., 2022.

[3]United States, Canada, Mexico, United Kingdom, Italy, France, Portugal, the Netherlands, Spain, Germany, Poland, Australia, New Zealand, and South Africa

vaccinated, 5 = prefer not to say. A binary *vaccination status* variable was created, distinguishing between those who were vaccinated (fully or partially) or not (including both those who were planning and not planning to get vaccinated in the future). Participants were asked to indicate frequency (on a scale from 1 = not at all to 5 = at least once an hour) of engaging in each of the following PHMs in the previous week: physical contact with people they do not live with, being in close proximity (i.e., closer than 2 meters apart) with people they do not live with, cleaning and disinfecting frequently touched surfaces (e.g., tables, doorknobs, light switches), cleaning hands with sanitizer or soap and water, and wearing a mask when outside of one's home. Two composite variables were created: *Physical distancing* (sum of reverse-coded physical contact and proximity items), and *cleaning* (sum of cleaning and disinfecting frequently touched surfaces and cleaning hands).

Delay Discounting Task

In this intertemporal choice procedure (Ciaramelli et al., 2021; Halilova et al., 2022; Mok et al., 2020), participants viewed pairs of monetary amounts and were asked to choose between smaller, immediate rewards which varied between trials, and a larger, delayed reward of $2,000. Participants were asked to make six choices at each of seven delays for the larger reward (waiting 1 week, 1 month, 3 months, 6 months, 1 year, 3 years, and 10 years before receiving the $2000 reward). An iterative, adjusting-amount procedure was used in which the amount of the immediate reward was increased or decreased based on the participant's previous choice at that delay, converging on the amount of the immediate reward equivalent in subjective value to the delayed reward. The first adjustment was half of the difference between the immediate and delayed amounts presented on the first trial, with each subsequent adjustment being half of the preceding adjustment. For example, in the condition where a future reward of $2000 could be received in 3 years, the first choice presented to the participants would be "$1000 right now or $2000 in 3 years." If the participant chose "$2000 in 3 years," the choice on the second trial would be "$1500 right now or $2000 in 3 years." If the participant then chose "$1500 right now", the choice on the third trial would be "$1250 right now or $2000 in 3 years." Following the sixth and final trial of each condition, the subjective value of the delayed reward was estimated as the amount of the immediate reward that would be presented on a seventh trial. A larger subjective value of the delayed reward indicated less discounting of delayed rewards. A smaller subjective value indicated a greater short-sighted bias in decision-making. Degree of discounting was measured by examining the subjective values of reward across the seven delays and computing *Area-under-the-Curve* (AuC), a single, theoretically-neutral measure of discounting (Myerson et al., 2001). Another advantage of using AuC as the measure of delay discounting is that it tends to generate approximately normally distributed scores (Myerson et al., 2001). The scores range from 0 to 1, with lower AuC representing a greater discounting rate (i.e., more short-sighted decision-making).

Demographic Questionnaire

Participants completed a demographic questionnaire assessing current country of residence, age, gender (female/male/non-binary), highest level of education obtained (primary schooling/secondary schooling/undergraduate degree or professional equivalent/postgraduate degree), essential worker status (yes/no), and personal income. For essential worker status, participants indicated if they worked in an occupation supplying critical services during the pandemic: government; health and safety (e.g., healthcare, emergency response); utilities (e.g., water, energy, sanitation, transport, communications); food (e.g., supermarkets); and manufacturing. A subjective measure of relative income was used, such that participants estimated their current income on a sliding scale (0-100) marked by points representing low (0), average (50), and high (100) incomes in their own country/region (Adler et al., 2000; Smith et al., 2019).

Psychological Distress Index

Presence and severity of anxiety and depressive symptoms were assessed with the Generalized Anxiety Disorder 7-item (GAD-7) scale (Spitzer et al., 2006) and the Patient Health Questionnaire 9-item (PHQ-9) scale (Kroenke et al., 2001), respectively. Participants rated the frequency of symptoms experienced over the past two weeks on a four-point scale (0 = not at all; 3 = nearly every day). The internal consistency remained the same as in the subsample of participants reported in Chapter 2; a = 0.88 and a = 0.92 for PHQ-9 and GAD-7, respectively. For each scale, a total score was computed, where higher scores reflect more severe symptoms. Total scores from these measures were standardized and then summed to create a *psychological distress index*.

Intolerance of Uncertainty Scale (IUS-12)

The IUS-12 is a 12-item measure of one's difficulties tolerating uncertainty (Carleton et al., 2007). Participants used a 5-point scale (1 = not at all characteristic of me; 5 = entirely characteristic of me) to respond to items measuring two factors of intolerance of uncertainty: prospective anxiety, the cognitive component of intolerance of uncertainty that indicates one's tendency to worry about future events (e.g., "I always want to know what the future has in store for me"); and inhibitory anxiety, the behavioral component of intolerance of uncertainty that represents avoidance tendencies in the face of uncertainty (e.g., "I must get away from all uncertain situations"; Carleton et al., 2007). The scale showed acceptable internal consistency (ω = 0.84). A detailed description of the factor analysis and estimation of internal consistency are provided in Appendix A. *Intolerance of uncertainty* score was calculated as a sum of participants' responses to IUS-12, ranging from 12 to 60.

Attention Checks

Three items from the Conscientious Responder Scale (CRS; Marjanovic et al., 2014) were included at select points within the survey to identify random responders (e.g., "To answer this question, please choose option three, neither agree nor disagree.").

Results

Vaccination

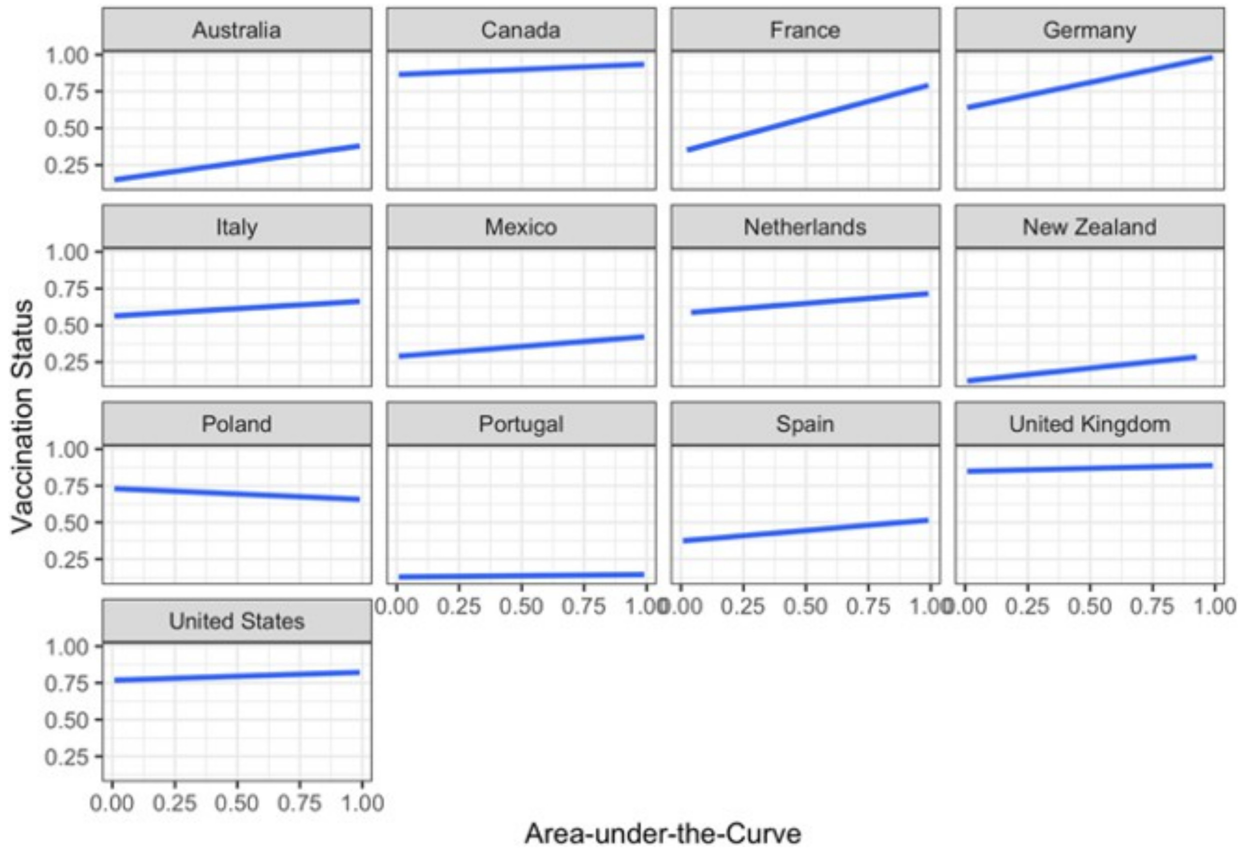
Two multilevel logistic models were constructed using R packages *lme4* (Bates et al., 2012) and *lmerTest* (Kuznetsova et al., 2017) with vaccination status (unvaccinated vs. vaccinated) as the outcome variable. The first model was constructed with AuC as the only predictor in the model to establish a zero-order effect. To account for possible systematic differences across countries (e.g., COVID-related severity, population vaccination rates, government response), each participant's vaccination status (Level 1) was nested within country (Level 2). AuC was positively associated with the likelihood of being vaccinated, OR = 1.75, 95% CI [1.32, 2.33]. The model was then expanded to test for the effect of AuC on vaccination status, after controlling for age, education level, income, essential workers status, psychological distress, and intolerance of uncertainty. The likelihood ratio test showed that the model accounted for significantly more variance in the data compared to an unconditional intercept-only model, $\chi^2(7) = 191.72$, $p < .001$. The tendency to choose larger future rewards over smaller immediate ones (larger AuC) significantly increased the odds of being vaccinated after controlling for other variables in the model ($p < .001$; Table 3.2). All of the control variables in the model positively predicted the likelihood of being vaccinated (p values < .05), with the exception of the psychological distress index ($p = .719$) and intolerance of uncertainty ($p = .154$), which were not significant predictors. The association between AuC and vaccination status was further explored by country. As evident in Figure 3.1, the association between AuC and vaccination status was stronger in countries where the participant vaccination rate was moderate (e.g., France, Germany, Italy, the Netherlands, Australia). In contrast, this association appears weaker in countries where the participant vaccination rate was either very high (e.g., Canada, United States, and United Kingdom) or very low (e.g., Portugal) in our sample represented by nearly horizontal lines at the top or bottom of the graphs in Figure 3.1, respectively. Poland appears to be the only country in our sample that showed a negative relationship between AuC and vaccination status.

Table 3.2 Results of the Multilevel Logistic Model Predicting Vaccination Status

Fixed Effects	*b*	*SE*	*z*	*p*	OR	95% CI
Intercept	-0.70	0.40	-1.78	.074	0.62	[0.29, 1.34]
Age†	0.27	0.04	7.49	<.001	1.31	[1.22, 1.40]
Education level	0.17	0.05	3.61	<.001	1.18	[1.08, 1.29]
Relative income†	0.07	0.03	2.01	.045	1.07	[1.00, 1.14]
Essential worker status	0.52	0.08	6.51	<.001	1.68	[1.44, 1.96]
Psychological distress†	†0.01	0.02	0.36	.719	1.01	[0.97, 1.05]
Intolerance of uncertainty†	0.05	0.03	1.43	.154	1.05	[0.98, 1.13]
Delay discounting (AuC)	0.57	0.12	4.62	<.001	1.15	[1.09, 1.22]
Random Effects	Estimate	*SD*				
Intercept error variance (country)	1.58	1.26				

Note. † The variable was scaled to improve model fit. AuC = Area-under-the-Curve. CI = Confidence interval; OR = odds ratio; SD = standard deviation; SE = standard error of the mean.

Figure 3.1 Vaccination Status by Area-under-the-Curve Across the 13 Countries



Note. Vaccination status (0 = unvaccinated, 1 = vaccinated) plotted by Area-under-the-Curve across the 13 countries from where the data were collected. The plots indicate generally positive relationships between the Area-under-the-Curve and vaccination status across countries, except for Poland where the relationship was negative.

Cleaning

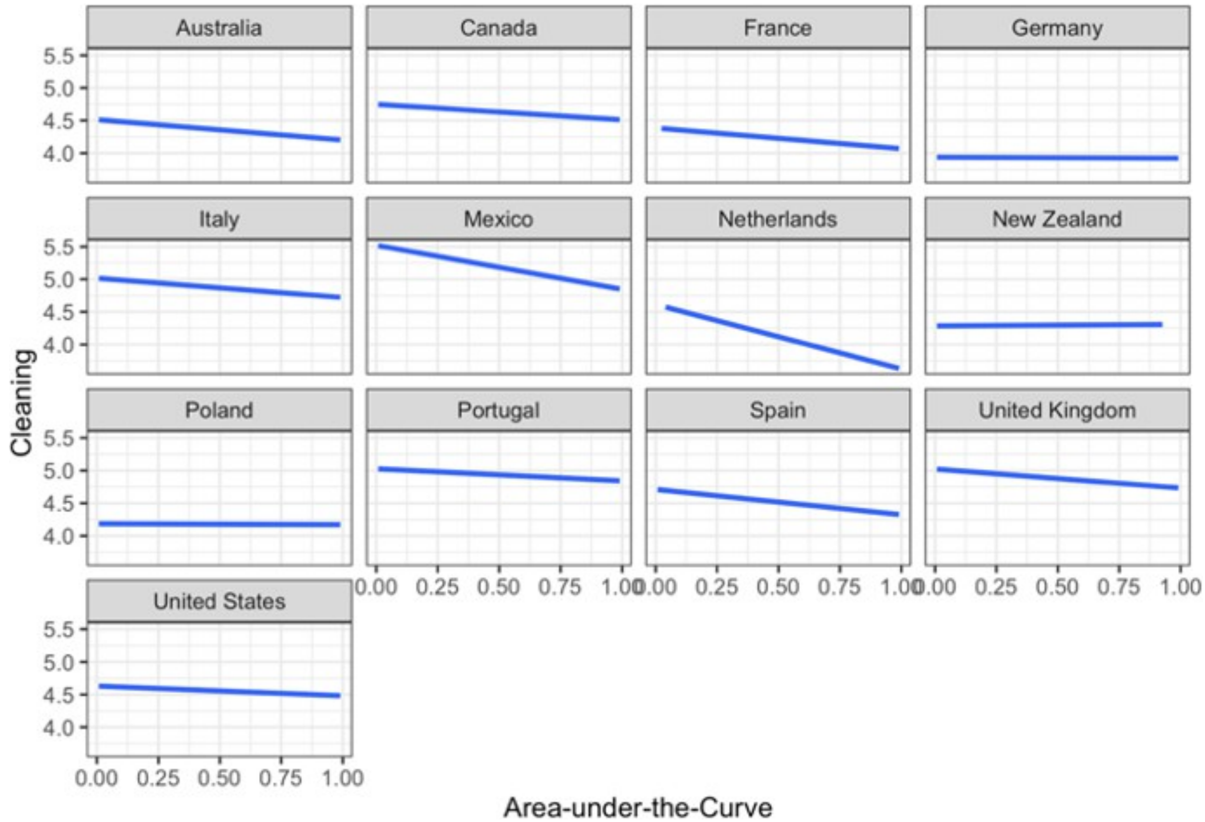
Two multilevel models were constructed with the cleaning composite score as the outcome variable. The first model was constructed with AuC as the only predictor in the model to establish a zero-order effect. Each participant's frequency of cleaning behaviors (Level 1) nested within country (Level 2). AuC negatively associated with the frequency of cleaning behaviors, b = -0.25, 95% CI [-0.39, -0.12]. The model was then expanded to test for the effect of AuC on vaccination status, after controlling for age, education level, income, essential workers status, psychological distress, and intolerance of uncertainty. The likelihood ratio test showed that the model accounted for significantly more variance in the data compared to an unconditional intercept-only model, $\chi^2(7) = 89.76$, $p < .001$. AuC negatively predicted the frequency of cleaning and handwashing after controlling for other variables in the model ($p <$ .001; Table 3.3), indicating that shorter-sighted thinking was associated with increased engagement in cleaning behaviours. In contrast, all of the control variables in the model positively predicted the frequency of engaging in cleaning behaviors, with essential worker status, psychological distress, and intolerance of uncertainty associated with a higher frequency of cleaning behaviors. The association between AuC and frequency of engaging in cleaning was further explored by country. As evident in Figure 3.2, the relationship between the variables was negative in 10 out of 13 countries, while there was no relationship between AuC and frequency of engaging in cleaning behaviors in Germany, New Zealand, and Poland.

Table 3.3 Results of the Multilevel Model Predicting Frequency of Cleaning Behaviors

Fixed Effects	Estimate	*SE*	*df*	*t*	*p*	95% CI
Intercept	4.55	0.15	46	30.78	< .001	[4.26, 4.84]
Age†	0.02	0.02	6849	1.32	.188	[-0.01, 0.06]
Education level	0.01	0.03	6850	0.54	.589	[-0.04, 0.07]
Relative income†	0.04	0.02	6845	2.35	.019	[0.01, 0.07]
Essential worker	0.18	0.04	6849	4.36	< .001	[0.10, 0.27]
Psychological distress†	0.05	0.01	6840	4.48	< .001	[0.03, 0.07]
Intolerance of uncertainty†	0.06	0.02	6841	2.80	.005	[0.02, 0.09]
Delay discounting (AuC)	-0.23	0.07	6847	-3.32	< .001	[-0.37, -0.10]
Random Effects	Estimate	*SD*				
Intercept error variance (country)	0.03	0.19				
Residual	0.50	0.71				

Note. † The variable was scaled to improve model fit. AuC = Area-under-the-Curve. CI = Confidence interval; SD = standard deviation; SE = standard error of the mean.

Figure 3.2 Frequency of Cleaning by Area-under-the-Curve Across the 13 Countries



Note. Frequency of cleaning behaviors, ranging from 0 to 8, plotted by Area-under-the-Curve across the 13 countries from where the data were collected. The plots indicate generally negative relationships between the Area-under-the-Curve and frequency of cleaning behaviors across countries, except for Germany, Poland, and New Zealand where there is no association between these variables.

Physical Distancing

The same approach to analysis was used to test the effect of AuC on engaging in physical distancing behaviors. First, the model was constructed with AuC as the only predictor in the model and physical distancing score as outcome to establish a zero-order effect. Each participant's frequency of physical distancing behaviors (Level 1) was nested within country (Level 2). AuC negatively associated with the frequency of cleaning behaviors, b = -0.25, 95% CI [-0.45, -0.05]. The model was then expanded to test for the effect of AuC on vaccination status, after controlling for age, education level, income, essential workers status, psychological distress, and intolerance of uncertainty. A likelihood ratio test shows that the model accounted for significantly more variance in the data compared to an unconditional intercept-only model,

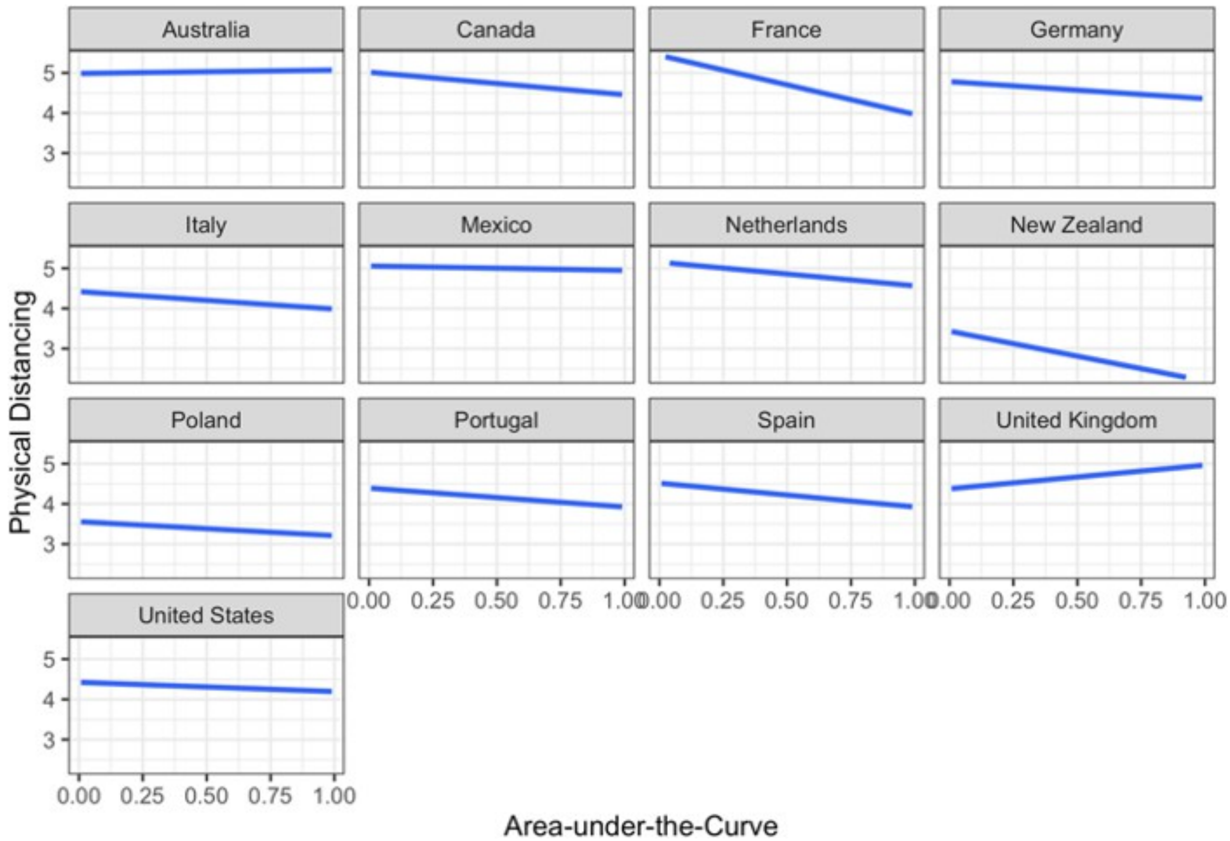
$\chi^2(7) = 460.07$, $p < .001$. Delay discounting (AuC) did not significantly predict the frequency of physical distancing after controlling for other variables in the model ($p = .212$; Table 3.4). Age, income, essential worker status, psychological distress, and intolerance of uncertainty significantly predicted the frequency of engaging in physical distancing (Table 3.4). The association between AuC and frequency of physical distancing behaviors was explored by country (Figure 3.3). The United Kingdom was the only country with a positive slope in the relationship between AuC and physical distancing; notably this was also the only country in the sample that did not have physical distancing restrictions in place during the time of data collection (Mathieu et al., 2020). Running the model again without the United Kingdom data resulted in AuC becoming a stronger negative predictor of frequency of physical distancing, $b = -0.23$, $SE = 0.11$, $t(5872) = -2.15$, $p = .032$, 95% CI [-0.44, -0.10], indicating that shorter-sighted thinking was associated with increased engagement in physical distancing. It was also notable that the associations between physical distancing and AuC were strongest in France, Spain, and Portugal (Figure 3.3), countries with the most stringent physical distancing mandates (i.e., stay-at-home was a requirement with the exception of essentials) in place during the time of data collection (Mathieu et al., 2020).

Table 3.4 Results of the Multilevel Model Predicting Frequency of Physical Distancing

Fixed Effects	Estimate	*SE*	*df*	*t*	*p*	95% CI
Intercept	4.38	0.23	35	19.14	< .001	[3.93, 4.83]
Age†	0.30	0.03	6848	11.05	< .001	[0.25, 0.35]
Education level	0.07	0.04	6849	1.88	.060	[-0.01, 0.14]
Relative income†	-0.13	0.03	6844	-5.06	< .001	[-0.19, -0.08]
Essential worker	-1.00	0.06	6847	-16.71	< .001	[-1.12, -0.89]
Psychological distress†	0.03	0.02	6840	2.17	.030	[0.01, 0.06]
Intolerance of uncertainty†	0.15	0.03	6841	5.27	< .001	[0.09, 0.02]
Delay discounting (AuC)	-0.12	0.10	6845	1.25	.212	[-0.32, 0.07]
Random Effects	Estimate	*SD*				
Intercept error variance (country)	0.38	0.62				
Residual	4.10	2.03				

Note. †The variable was scaled to improve model fit. AuC = Area-under-the-Curve. CI = Confidence interval; SD = standard deviation; SE = standard error of the mean.

Figure 3.3 Frequency of Physical Distancing by Area-under-the-Curve Across the 13 Countries



Note. Frequency of physical distancing behaviors, ranging from 0 to 8, plotted by Area-under-the-Curve across the 13 countries from where the data were collected. The plots indicate generally negative relationships between the Area-under-the-Curve and frequency of cleaning behaviors across countries, except for United Kingdom, where the relationship between the variables is positive.

Mask-Wearing

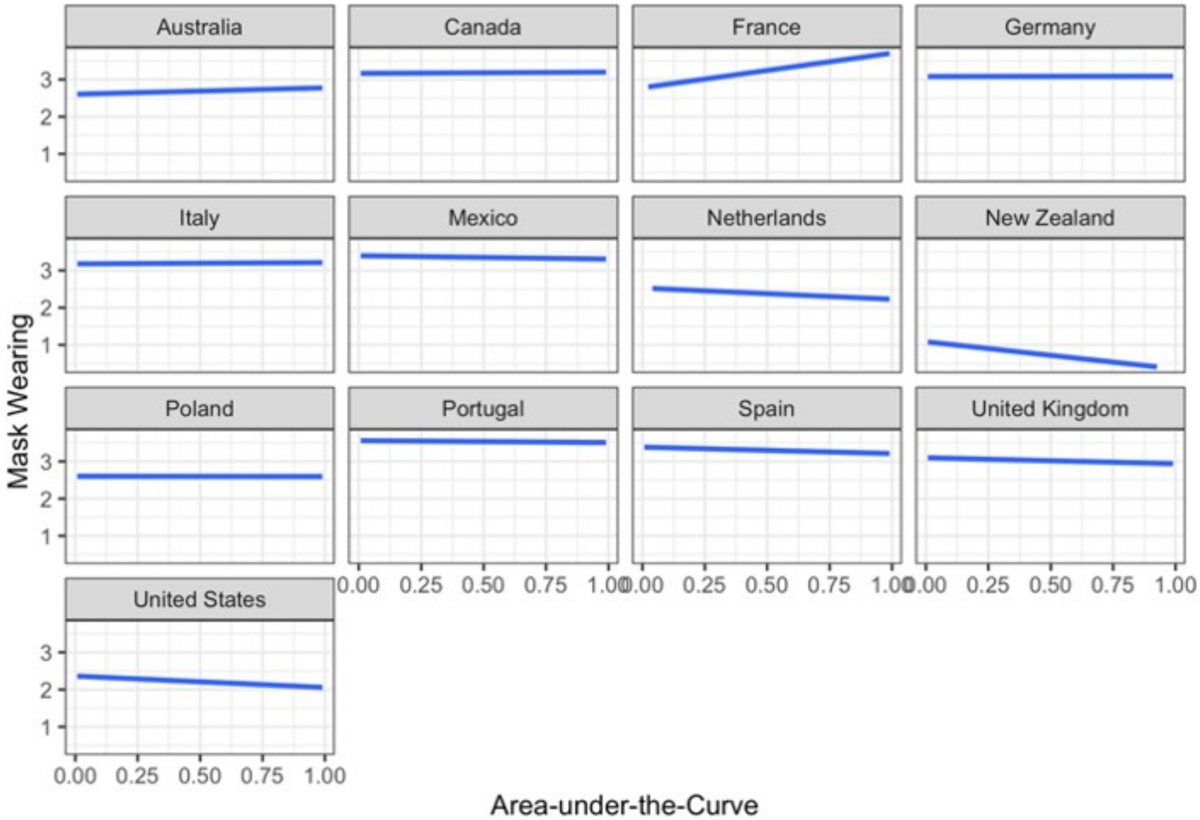
The same approach to analysis was used to test the effect of AuC on mask-wearing. First, the model was constructed with AuC as the only predictor in the model and frequency of mask-wearing as outcome to establish a zero-order effect. Each participant's frequency of mask-wearing (Level 1) was nested within country (Level 2). There was no association between AuC and frequency of mask-wearing, b = -0.08, 95% CI [-0.19, 0.02]. The model was then expanded to test for the effect of AuC on vaccination status, after controlling for age, education level, income, essential workers status, psychological distress, and intolerance of uncertainty. The likelihood ratio test showed that the model accounted for significantly more variance in the data compared to an unconditional intercept-only model, $\chi^2(7) = 103.43$, $p < .001$. Delay discounting (AuC) did not predict the frequency of mask-wearing after controlling for other variables in the model ($p = .185$; Table 3.5). Among control variables, education level, essential worker status, and psychological distress were significant positive predictors of frequency of mask-wearing. On the other hand, age was a significant negative predictor of mask-wearing in the model. The association between AuC and frequency of mask-wearing was explored by country (Figure 3.4). There were no strong relationships between delay discounting and mask wearing among participants from most countries in our sample. In our sample, France and New Zealand appear as the countries with the strongest associations between AuC and mask-wearing, positive and negative, respectively. However, the association is not significant when fitting the model with the same set of control variables individually for these countries (for France, $b = 0.81$, $p = .06$ and for New Zealand, $b = -0.66$, $p = .09$).

Table 3.2 Results of the Multilevel Model Predicting Frequency of Mask-Wearing

Fixed Effects	Estimate	*SE*	*df*	*t*	*p*	95% CI
Intercept	2.55	0.21	16	11.98	< .001	[2.12, 2.98]
Age†	-0.04	0.01	6842	-2.45	< .001	[-0.07, -0.01]
Education level	0.07	0.02	6842	3.18	.002	[0.03, 0.11]
Relative income†	-0.01	0.01	6840	-0.01	.989	[-0.03, 0.03]
Essential worker	0.21	0.03	6841	6.46	< .001	[0.15, 0.28]
Psychological distress†	0.04	0.01	6839	4.47	< .001	[0.02, 0.05]
Intolerance of Uncertainty†	0.03	0.02	6839	1.64	.101	[-0.01, 0.06]
Delay discounting (AuC)	-0.07	0.05	6841	-1.32	.185	[-0.18, 0.03]
Random Effects	Estimate	*SD*				
Intercept error variance (country)	0.50	0.71				
Residual	1.23	1.11				

Note. † The variable was scaled to improve model fit. AuC = Area-under-the-Curve. CI = Confidence interval; OR = odds ratio; SD = standard deviation; SE = standard error of the mean.

Figure 3.4 Frequency of Mask-Wearing by Area-under-the-Curve Across the 13 Countries



Note. Frequency of mask-wearing behavior, ranging from 0 to 4, plotted by Area-under-the-Curve across the 13 countries from where the data were collected. The plots indicate generally no significant relationships between the Area-under-the-Curve and frequency of mask-wearing behavior across countries.

Discussion

The current research investigated delay discounting as a predictor of PHMs, including protective behaviors with more delayed benefits (i.e., vaccination) and those with more immediate benefits (i.e., cleaning, physical distancing, and mask wearing). A large multinational sample allowed us to detect differences in PHM compliance across 13 countries. As predicted, discounting of delayed rewards was a significant positive predictor of vaccination status: individuals who tend to choose more delayed rewards over smaller immediate rewards (i.e., far-sighted thinking) were more likely to be vaccinated (see also Halilova et al., 2022). Delay discounting was a significant predictor of the frequency of cleaning and handwashing behaviors. Also as predicted, the direction of the relationship was opposite to that for vaccination: individuals who tend to choose more immediate rewards over larger later rewards (i.e., near-sighted thinking) engaged in cleaning behaviors more frequently. Like cleaning, near-sighted thinking was also a significant positive predictor of physical distancing. This effect was evident for all countries except the United Kingdom, where delay discounting was instead a negative predictor of physical distancing. Interestingly, this was the only country in our sample where there were no physical distancing mandates in place during the time of data collection (Mathieu et al., 2020). Lastly, delay discounting did not significantly predict likelihood of mask-wearing over and above the control variables.

The association between delay discounting and COVID-19 vaccination status extends recent findings in a subsample of the participants tested in the current study (Halilova et al., 2022) and is consistent with findings from other recent studies on the topic (Hudson et al., 2022; Strickland et al., 2022). The results are also consistent with research showing that even though nonmonetary outcomes (e.g., health) are generally discounted more steeply than monetary outcomes (Baker et al., 2003; Odum et al., 2020), discounting has trait-like qualities and may be context-independent (Odum et al., 2020). These findings suggest the importance of considering delay discounting as the target of interventions that train people to place greater value on future rewards (Scholten et al., 2019). Encouraging people to imagine personally-relevant future events has previously been shown to reduce one's discounting of delayed rewards (Bromberg et al., 2017; Ciaramelli et al., 2021; Mok et al., 2020; Rung & Madden, 2018) and is among the most promising discounting interventions (Scholten et al., 2019). Future research focused on cueing future events to counteract the temporal delay of vaccination will be informative for public health mandates in relation to containment of infectious diseases.

The findings were somewhat more mixed when it comes to other PHMs. As hypothesized, the tendency to choose more immediate smaller rewards over larger later rewards predicted more frequent cleaning and handwashing behaviors across most countries. This association between greater near-sighted thinking and cleaning behaviors during COVID-19 suggests that focusing on the present moment may be most helpful when choosing to engage in behaviors that have more immediate protective outcomes. We also found that the tendency to choose immediate smaller rewards over larger later rewards predicted more frequent engagement in physical distancing behaviors during COVID-19, after the United Kingdom was excluded from the analysis due to the absence of physical distancing mandates. The findings are consistent with previous research showing a positive association between near-sighted thinking and willingness to engage in immediate protective measures (Calluso et al., 2021; Wismans et al., 2021). Although unexpected, the finding of a negative relationship between near-sighted decision-making and physical distancing in the United Kingdom, where there were no physical distancing restrictions in place at the time of data collection in 2021, is also consistent with previous findings in a UK sample (Lloyd et al., 2021). It may be that when free to exercise personal choice over whether to physically distance or not, different factors are considered than when deciding to comply with PHMs that are mandated. Moreover, the removal of mandates may signal that immediate safety concerns have resolved and, thus, perhaps it is not surprising that people who tended to engage in physical distancing in this context were the ones who discounted the future less (i.e., those who tended to prioritize longer-term rewards).

Although unexpected, the nonsignificant relationship between mask-wearing and delay discounting is consistent with some previous findings (Krawiec et al., 2022), but not others (Byrne et al., 2021; Calluso et al., 2021). One explanation is that compared to others protective measures (e.g., physical distancing and handwashing), mask-wearing mandates are socially enforced as non-compliance is easily detectable, thereby restricting people's freedom of choice relating to compliance with this PHM. For example, if one is not wearing a mask in a hospital where masks are required, one may be asked to either put on their mask or be denied service. On the other hand, monitoring and enforcing compliance with physical distancing in public venues may be a greater challenge. Compliance with physical distancing, cleaning, and handwashing may therefore depend to a greater extent on one's decision-making process than compliance with mask-wearing.

Another possible explanation for different patterns of delay discounting across different PHMs is the cost of engaging in protective behaviors in the present moment (Petherick et al., 2021). Given that mask-wearing is a relatively low-cost protective behavior, individuals may readily implement it without needing to assess the short- and long-term costs and benefits of that behavior. On the other hand, physical distancing may be viewed as a higher-cost behavior that requires one to assess costs and benefits of avoiding interacting with others (e.g., missing an important event, working remotely). Similarly, cleaning and handwashing behaviors may be more time consuming (i.e., costly) to engage in and require an assessment of costs and benefits (e.g., spending the time engaging in other more enjoyable activities).

The multinational nature of the sample also allowed us to examine the relationship between delay discounting and frequency of engaging in PHMs across countries, helping to reconcile discrepancies in previous studies and begin to understand other factors influencing compliance with protective behaviors (e.g., government mandates). For example, examining the relationship across all of the PHMs in the current study, it appears that in Poland there is almost no association between discounting of delayed rewards and PHM compliance, which is consistent with previous literature (Krawiec et al., 2022). This discrepant finding suggests the need for further investigation of the impact of economic and cultural factors that have been previously found to influence delay discounting on PHM compliance (Du et al.., 2002; Ishii et al., 2016; Ruggeri et al., 2022).

Overall, delay discounting is a cognitive bias that predicts compliance with most COVID-related PHMs, including vaccination, cleaning and handwashing, and physical distancing. Temporal delay of protective benefits of PHMs may determine the direction of the relationship between delay discounting and decisions to engage in the PHMs. Given that delay discounting is a modifiable characteristic, future research should focus on investigating the effectiveness of different interventions targeting delay discounting (e.g., cuing individuals to imagine the future; Ciaramelli et al., 2021; Mok et al., 2020) to improve the compliance with various PHMs. The findings inform future policies designed to encourage PHM compliance and reinforce the utility of behavioral economic measures in orienting people towards making healthier choices that have global societal benefits.

In Chapters 2 and 3, delay discounting was tested as a predictor of vaccination and other COVID-19 protective behaviors. It was found that individuals who tend to favour smaller more immediate rewards over larger later rewards are more likely to engage in PHMs such as physical distancing and cleaning, but are less likely to have received a main dose of the COVID-19 vaccine. However, the decision to get vaccinated is a complex process with many contributing variables. In Chapter 4, we focus on longitudinal dynamic of the vaccination decisions. The emphasis is placed on understanding predictors of maintaining long-term immunity under conditions of non-mandatory vaccination. Specifically, we investigate delay discounting as a predictor of willingness to receive a COVID-19 vaccine booster dose in June-August 2022 among those who at that time reported having been vaccinated with at least one main dose of the COVID-19 vaccine.

Chapter 4: Delay Discounting Predicts COVID-19 Vaccine Booster Willingness

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In the wake of the COVID-19 pandemic that swept the world, and with new variants and infectious diseases on the horizon, it is imperative to reflect on lessons learned during COVID-19 to prepare for future public health crises. Behavioural science has a critical role to play in this endeavour, as the decisions and behaviours of individuals determine the success of many public health strategies. Throughout the course of the COVID-19 pandemic, recommended protective behaviors have undergone dynamic shifts in response to the evolving landscape of the crisis. The early response heavily leaned on government mandates, compelling individuals to adhere to public health measures such as physical distance, mask-wearing, and stringent hand hygiene, to be able to engage in social interactions, work, and travel. As vaccines were subsequently developed and rolled out, the focus pivoted towards promoting widespread vaccination to achieve population-level immunity, again often with the use of mandates. With the pandemic transitioning from an acute emergency to a managed state, booster doses are recommended to sustain immunity over time, but individuals now have more autonomy over the decision to receive booster doses. This decision also needs to be made repeatedly, with the roll out of new boosters annually. Continuous vaccination plays a pivotal role in preventing the resurgence and rapid spread of infectious diseases by maintaining widespread immunity within communities (Greenwood, 2014) and limiting pathogen transmission (Feldman et al., 2021; Greenwood, 2014; Pollard & Bijker, 2021). Thus, understanding the determinants that shape the decision to receive additional booster doses is of crucial importance to encourage sustained maintenance of public health in the long run.

Worldwide the uptake of vaccine booster doses has shown a notable disparity from rates of initial vaccination (e.g., Dziedzic et al., 2022; Limbu & Huhmann, 2023; Lin et al., 2023). Only around 50% of those who had received their primary vaccine doses opted to pursue booster shots (Lin et al. in 2023). This discrepancy raises questions about the distinct nature of decision-making between the primary and booster vaccine doses. With the emergence of new COVID-19 variants (e.g., BA2.86, EG.5), it is particularly important to ensure sustained public immunity (Lazarus et al., 2023) by maximizing the effectiveness of public health strategies targeting vaccine booster behavior. However, vaccine hesitancy is a complex issue influenced by various factors, including cognitive biases, social norms, and economic considerations. Previous research has shown that COVID-19 vaccine booster hesitancy is predicted by gender (female), age (younger), and education level (lower level of education; Noh et al., 2022; Paul & Fancourt, 2022), health status (those without pre-existing health conditions; Paul & Fancourt, 2022), low level of worry about COVID-19 (Paul & Fancourt, 2022), lower socio-economic status (Paul & Fancourt, 2022), pregnancy (Attia et al., 2022), history of previous COVID-19 infection (Attia et al., 2022), as well as perceived risks, benefits, and vaccination barriers (Qin et al., 2022).

The role of behavioral economic measures in predicting vaccine booster hesitancy remains underexplored, despite their well-documented utility in public health policy (e.g., Matjasko et al., 2016; Ruggeri, 2022; van Bevel et al., 2020). The current research contributes to the literature on booster hesitancy by investigating the role of delay discounting, a behavioral economic measure of one's tendency to favour smaller immediate rewards over larger later rewards (Green & Myerson, 2004). Delay discounting has been shown to be a reliable predictor of engagement in a wide range of health-related behaviors, including healthy dietary habits (Appelhans et al., 2019), physical exercise (Albelwi et al., 2019), smoking cessation (e.g., Baker et al., 2003; Bickel et al., 1999), substance use (MacKillop et al., 2011), and more recently, the decision to get vaccinated during the COVID-19 pandemic (Halilova et al., 2022; Hudson et al., 2022). Importantly, delay discounting is a modifiable trait variable (Odum, 2011), which makes it a target mechanism of public health interventions with a variety of potential health benefits. For example, previous research has shown that cueing individuals to imagine future personally relevant specific events leads to a reduced rate of discounting of delayed rewards (Bromberg et al., 2017; Ciaramelli et al., 2021; Mok et al., 2020; Rung & Madden, 2018). In the realm of delay discounting related to vaccination, understanding the reward context (i.e., reasons for vaccine booster willingness and hesitancy) is crucial for examining how individuals weigh immediate versus delayed rewards when making decisions about vaccination. Insights into delay discounting patterns and reasons for vaccine booster willingness may inform public health policies to promote vaccine booster willingness (e.g., campaigns that appeal to public trust versus implementing mandates; Goldenberg et al., 2023).

In this longitudinal study, we test the potential utility of delay discounting among those who received the main dose of the COVID-19 vaccine as a predictor of their booster vaccine hesitancy a year later. Specifically, we examine delay discounting (measured by performance on a behavioral task) as a predictor of subsequent booster willingness after controlling for factors that have previously been shown to predict vaccination status, such as age (e.g., Guay et al., 2022), education level (Guay et al., 2022), relative income (Larkin, 2022), essential worker status (Lavoie et al., 2022), psychological distress (Penner et al., 2023), and intolerance of uncertainty (Brun et al., 2022). We also assessed reward context related to vaccine booster willingness and hesitancy by asking participants to describe reasons for their decisions.

Method

Participants

Participants were recruited through an online platform (Prolific.co) between June 2021 and August 2021 to participate in Part 1 of a larger longitudinal study[4]. Using Prolific's built-in inclusion/exclusion filters, the study was available only to Prolific users meeting the following inclusion criteria: aged 18 years or older, fluent in English, normally residing in one of 13 target countries[5] across North America, Europe, Australasia, and free from neurological impairments or learning disabilities. Approximately one year later, participants who completed Part 1 were invited to participate in Part 2 between June 28, 2022 and August 28, 2022. A total of 3,185 individuals completed both Part 1 and Part 2 of the study. As this study focuses on booster hesitancy in individuals who have received the main dose of the COVID-19 vaccine, the 270 participants who reported being unvaccinated in Part 2 were excluded, as were the 368 who did not provide a response to the question about vaccine boosters (the outcome variable of interest).

The final data set was composed of 2,547 participants who were on average 30.92 (*sd* = 11.42) years old; 1417 were female, 1075 male, 51 non-binary, and 4 preferred not to respond. Approximately 30% of the sample had achieved secondary level education, 49% had an undergraduate degree, and 20% of the sample achieved postgraduate education. Approximately 22% of the sample self-identified as essential workers, working in occupations supplying critical services during the pandemic: government; health and safety (e.g., healthcare, emergency response); utilities (e.g., water, energy, sanitation, transport, communications); food (e.g., supermarkets); and manufacturing. Given the international nature of our sample, we used a subjective measure of relative income where participants estimated their current income relative to others in their own country/region on a sliding scale with three anchors (0 = low, 50 = average, 100 = high; Adler et al., 2000; Smith et al., 2019); the average relative income was

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[4]The sample of those who participated in Part 1 of the study in 2021 has been reported in Chapter 2 and 3.
[5]United States, Canada, Mexico, United Kingdom, Italy, France, Portugal, the Netherlands, Spain, Germany, Poland, Australia, and New Zealand

38.83 (*sd* = 23.8). Approximately 19% of the sample (484 participants) indicated during Part 2 that they would choose not to receive a vaccine booster dose, if one was recommended.

The study was approved by the York University and Baycrest Research Ethics Boards for research with human participants, and all research was conducted in accordance with the Declaration of Helsinki. All the participants provided informed online consent prior to their participation in the study. Anonymized, raw and cleaned data as well as code necessary to reproduce the results have been deposited in a public repository hosted by the Open Science Framework (https://osf.io/z932y/?view_only=87123c53ebbf470082f24bdf6d7ad557).

Measures

Vaccination Status and Booster Willingness

First, we identified those participants who, at the time of completing Part 2, had received at least one dose of the COVID-19 vaccine. Participants were asked to indicate their vaccination status using the same question used in Part 1 of the study (see Halilova et al., 2022). Participants chose between 5 options to indicate their vaccination status: 1 = yes, I have received all necessary doses; 2 = yes, although I require another dose; 3 = no, but I am planning to get vaccinated; 4 = no, I am not planning to get vaccinated; or 5 = prefer not to say. A binary *vaccination status* variable was created, distinguishing between those who were vaccinated (fully or partially) or not (including both those who were planning and not planning to get vaccinated in the future). Those who indicated receiving at least one dose (i.e., options 1 or 2) were then asked the following question to assess booster willingness: *"If another dose of the COVID-19 vaccine was recommended, would you choose to receive it?"* Participants responded using the following scale: 0 = no, 1 = yes, or 2 = prefer not to say.

Reasons for Booster Willingness and Hesitancy

Participants had the opportunity to explain their reason(s) for their choice about willingness to get a vaccine booster dose if one was recommended. Participant responses were scored according to the primary reason described, using the categories of vaccination reasons developed by Halilova et al. (submitted): (1) ending or containing the pandemic (e.g., "it would help fight the pandemic"), (2) protecting oneself or others from COVID-19 (e.g., "to be safe and keep others safe as well"), (3) (non-)necessity (e.g., "for regulatory and travel purposes"), (4) (mis)trust (in science, government, or vaccines; e.g., "not enough evidence that vaccines are safe"), (5) health reasons (e.g., "medical complications", "bad side effects from the vaccinations”), or (6) other (e.g., “I am afraid of needles”). To establish inter-rater reliability, S.F.C. and two independent raters (W.F. and R.T.) scored mentions of these reasons in 100 randomly-selected participant responses (responses could have more than one reason). Raters had 86-87% agreement with S.F.C. on their categorizations of reasons and acceptable inter-rater reliability (Cohen’s Kappa = .92 - .93). The two independent raters then scored all of the responses from the participants reported on in this paper.

Delay Discounting Task

In this intertemporal choice paradigm (Ciaramelli et al., 2021; Halilova et al., 2022; Mok et al., 2020), participants were presented with pairs of monetary values and tasked with deciding between immediate, smaller rewards that changed from trial to trial, and a larger, later reward of $2,000. Each participant had to make six decisions at seven distinct temporal delays for the larger reward (1 week, 1 month, 3 months, 6 months, 1 year, 3 years, and 10 years before receiving the $2,000 reward). The process employed an iterative approach in which the value of the immediate reward was modified based on the participant’s prior decision at a particular delay. This adjustment aimed to converge on an immediate reward value equivalent in subjective worth to the delayed reward. The initial adjustment was set at half the difference between the immediate and delayed amounts offered in the initial trial. Subsequent adjustments were consistently half of the preceding values. For instance, in a scenario where a future $2,000 reward could be obtained in 3 years, the participant’s initial choice would be between “Receive $1,000 now or $2,000 in 3 years.” Should the participant select “$2,000 in 3 years,” the subsequent choice would be between “$1,500 now or $2,000 in 3 years.” If the participant then opted for “$1,500 now,” the subsequent choice would present “$1,250 now or $2,000 in 3 years.” After the completion of the sixth and final trial for each condition, the subjective value of the delayed reward was estimated as the immediate reward amount for a hypothetical seventh trial. A higher subjective value for the delayed reward indicated a lesser discounting rate, while a lower value represents a greater tendency for short-sighted decision-making. The degree of discounting was quantified by analyzing the subjective values of the rewards across the seven delays and calculating the Area-under-the-Curve (AuC), which is a single, neutral measure of discounting (Myerson et al., 2001). The discounting measure of AuC also has the benefit of generating approximately normally distributed scores (Myerson et al., 2001). These scores range from 0 to 1, where a lower AuC value represents a more pronounced discounting rate (i.e., greater tendency for short-sighted decision-making). Given that delay discounting is a relatively stable individual characteristic (Odum, 2011), discounting scores obtained in Part 1 of the study were used as predictors of booster willingness in Part 2 of the study.

Psychological Distress Index

Presence and severity of anxiety and depressive symptoms were assessed with the Generalized Anxiety Disorder 7-item (GAD-7) scale (Spitzer et al., 2006) and the Patient Health Questionnaire 9-item (PHQ-9) scale (Kroenke et al., 2001), respectively. Participants rated the frequency of symptoms experienced over the past two weeks on a four-point scale (0 = not at all; 3 = nearly every day). Both scales showed strong internal consistency (see Chapter 3). For each scale, a total score was computed, where higher scores reflect more severe symptoms. The total scores for these measures strongly correlated ($r = 0.78$). The totals were standardized and then summed to create a *psychological distress index*.

Intolerance of Uncertainty Scale (IUS-12)

The IUS-12 is a 12-item measure of one's difficulties tolerating uncertainty (Carleton et al., 2007). Participants used a 5-point scale (1= not at all characteristic of me; 5= entirely characteristic of me) to respond to items measuring two factors of intolerance of uncertainty: prospective anxiety, the cognitive component of intolerance of uncertainty that indicates one's tendency to worry about future events (e.g., "I always want to know what the future has in store for me") and inhibitory anxiety, the behavioral component of intolerance of uncertainty that represents avoidance tendencies in the face of uncertainty (e.g., "I must get away from all uncertain situations"; Carleton et al., 2007). The scale showed acceptable internal consistency ($\omega = 0.86$). A detailed description of the factor analysis and estimation of internal consistency are provided in Appendix A. *Intolerance of uncertainty* score was calculated as a sum of participants' responses to IUS-12, ranging from 12 to 60.

Attention Checks

To identify random responders, three items from the Conscientious Responder Scale (Marjanovic et al., 2014) were included at select points within the survey in Part 1 (e.g., "To answer this question, please choose option three, neither agree nor disagree."). In Part 2, only one item was included given that this survey was much shorter. None of the participants in the current subsample failed the attention check.

Procedure

Data were collected on the above measures using two online Qualtrics surveys, as part of a larger longitudinal study. During Part 1 (between June and August 2021), among other measures, participants provided informed consent, demographic information, and completed the GAD-7, PHQ-9, IUS-12, the delay discounting task, as well as indicated their COVID-19 vaccination status. During Part 2 (between June and August 2022), among other measures, participants responded to a series of COVID-related questions, including their vaccination status, as well as their willingness to get a vaccine booster dose if one was recommended.

Results

Booster Willingness

Approximately 81% of the sample (2063 participants) indicated that they were willing to receive a vaccine booster dose. Two multilevel logistic models were constructed using R packages *lme4* (Bates et al., 2012) and *lmerTest* (Kuznetsova et al., 2017) with booster willingness at *Time 2* (no vs. yes) as the outcome variable. The first model was constructed with AuC as the only predictor in the model to establish a zero-order effect. To account for possible systematic differences across countries, each participant's booster willingness (Level 1) was nested within country (Level 2). AuC was positively associated with the likelihood of being vaccinated, OR = 1.75, 95% CI [1.17, 2.63]. The model was then expanded to test for the effect of AuC on booster willingness, after controlling for age, education level, income, essential workers status, psychological distress, and intolerance of uncertainty. The likelihood ratio test showed that the model accounted for significantly more variance in the data compared to an unconditional intercept-only model, $\chi^2(7)$
$= 25.60$, $p < .001$.

Table 4.1 Results of the Multilevel Logistic Model Predicting Booster Willingness

Fixed Effects	*b*	*SE*	*z*	*p*	OR	95% CI
Intercept	0.91	0.35	2.62	.009	2.47	[1.26, 4.87]
Age†	0.01	0.01	1.46	.144	1.01	[1.00, 1.02]
Education level	0.02	0.08	0.30	.763	1.02	[0.88, 1.19]
Relative income†	-0.15	0.06	-2.70	.007	0.86	[0.77, 0.96]
Essential worker status	-0.08	0.13	-0.63	.529	0.92	[0.72, 1.18]
Psychological distress†	0.09	0.03	2.71	.007	1.10	[1.03, 1.17]
Intolerance of uncertainty†	-0.08	0.06	-1.32	.186	0.92	[0.82, 1.04]
Delay discounting (AuC)	0.65	0.21	3.07	.002	1.92	[1.27, 2.91]
Random Effects	Estimate	*SD*				
Intercept error variance (country)	0.17	0.41				

Note. † The variable was scaled to improve model fit. AuC = Area-under-the-Curve. CI = Confidence interval; OR = odds ratio; SD = standard deviation; SE = standard error of the mean.

The tendency to choose larger future rewards over smaller immediate ones, represented by greater AuC, increased the odds of being willing to get a booster vaccine dose after controlling for other variables in the model (OR = 1.92, 95% CI [1.27, 2.91], p = .002; Table 4.1). Among control variables in the model, only relative income and psychological distress predicted willingness to get a vaccine booster dose if one was recommended ($p < .05$; Table 4.1). Controlling for other variables in the model, individuals who rated themselves higher on the measure of relative income were less likely to be willing to get a vaccine booster dose if one was recommended, OR = 0.86, 95% CI [0.77, 0.96]. Controlling for other variables in the model, individuals who reported experiencing more psychological distress were more likely to be willing to get a vaccine booster dose if one was recommended, OR = 1.10, 95% CI [1.03, 1.17].

Reasons for Booster Willingness and Hesitancy

In Part 2, 2536 participants provided reasons why they would (n = 2,054) or would not (n = 482) be willing to receive a vaccine booster dose if one was recommended. Of those willing to receive a vaccine booster, 59% reported protection against COVID-19 as their reason (40% for themselves, 5% for their families, and 14% for others). 26% reported that their booster willingness was based on trust (12% trust in science, 10% in vaccines, and 4% in government/authorities). Additional reasons for a willingness to get a booster included necessity (7%, e.g., for social, work or ethical reasons), ending or containing the pandemic (3%), health reasons (1%), and "other" responses which did not belong to any aforementioned category (4%; e.g., "Why not").

Of the 482 participants who indicated they were unwilling to receive a vaccine booster, 24% based their decision on mistrust (18% in vaccines, 1% in science and 1.5% government/authorities, with 3.5% reporting a general mistrust). Other reported reasons included non-necessity (53%), adverse health risks (15%), and having sufficient current protection (2.49%), and "other" responses (5%; e.g., "I see no reason to take it").

Discussion

In the current research, we investigated delay discounting as a predictor of COVID-19 vaccine booster willingness. The result that individuals who are better able to delay gratification (i.e., engage in less delay discounting) are more willing to get vaccinated with a booster dose if one is recommended is consistent with previous literature on delay discounting and engagement in health-related behaviors (e.g., Daugherty & Brase, 2010; Robles et al., 2012) including vaccines (e.g., Freitas-Lemos et al., 2023; Halilova et al., 2022). Importantly, we found that delay discounting was a predictor of willingness to get a vaccine booster dose, even after statistically accounting for the effects of demographic and emotional factors that have previously been shown to predict vaccine hesitancy.

Our findings enhance the understanding of the decision-making process related to COVID-19 booster vaccine doses and suggest that, in order to maintain long-term population immunity against the virus, strategies should focus on encouraging people to think more about the delayed benefits of vaccination. The reasons provided by participants for their booster decisions also offer interesting insights, and suggest ways that public health campaigns and educational initiatives could be more effective. It might be necessary to consider two broad categories of interventions: one type that emphasizes and highlights the reasons mentioned by the participants who expressed *willingness* to receive a booster dose, and another type that deemphasizes or resolves the concerns mentioned by participants *unwilling* to receive a booster. The majority of those who were willing expressed the desire to protect themselves and others as the primary reason, which is consistent with previous research on the role of empathy and social norms in vaccination (Drazkowski et al., 2022). This suggests that an effective approach should combine societal concern with interventions designed to reduce delay discounting and promote longer term thinking. For instance, emphasizing the longer-term benefits of boosters in protecting communities may effectively increase the salience of delayed societal rewards. Existing interventions that cue individuals to imagine personally-relevant future events to reduce delay discounting (Ciaramelli et al., 2022; Mok et al., 2021) could be modified to involve collective future events facilitated by the protection afforded by boosters. Our study also indicates that future research focusing on mechanisms and mediation models should investigate the reasons *why* people engage in these protective health behaviours, so that public health campaigns can target these reasons.

In addition to advancing knowledge of the predictors of willingness to get boosters, our results offer insights into why some people are unwilling to receive boosters. Over 50% of our participants who decided against a booster explained that they believed it was unnecessary. Given the known risks to health from an infection (e.g., Del Rio et al., 2020; Khaswal et al., 2022), biased risk perception appears to be a factor in the unwillingness to receive boosters, and may underlie our finding that delay discounting predicts such unwillingness. It is notable that the current research was conducted with individuals who were already vaccinated with at least one dose, suggesting potential discrepancies in the perceived risk of the main versus booster doses. From a public health perspective, this observation suggests that, in addition to emphasizing social norms, it is also necessary to address the biased perception of risk (e.g., Sinclair et al., 2023). For example, the fact that majority of people believe that the vaccine boosters are necessary and that boosters will protect them and others from the virus in the long-term could be highlighted.

Examining ways of correcting biased risk perception could be an important avenue of future research. For example, the deliberation process likely involves weighing the more immediate risks of side effects with the relatively delayed risks posed by possible infection. Indeed, Limbu and Huhmann's (2023) framework for booster vaccine hesitancy posits that booster complacency reflects a lack of concern about COVID-19, biased perception of the health risks, as well as the perceived benefits and efficacy of boosters. Delay discounting likely contributes to booster complacency given that one's tendency to discount the future likely influences risk perception when it comes to COVID-19 and vaccination (Jiang & Dai, 2021). Taken together with the current findings, it suggests that in addition to providing people with information about COVID-19 and benefits of vaccination, public health campaigns should present that information in way that corrects for the biased perception of risk captured by cognitive phenomena like delay discounting.

Mistrust in the vaccine was another common reason for not getting a booster, mentioned by approximately 25% of those unwilling. This finding suggests the need to improve the public's faith in vaccines, particular once vaccines become non-mandated. In times of rapid mobilization, like the COVID-19 pandemic, direct interventions like government mandates (e.g., lockdowns and travel restrictions) that bypass cognitive processes prove most effective in eliciting short-term behavioral changes (Brewer et al., 2017; Broomell & Chapman, 2021). However, it is possible that despite such short-term effectiveness, the rapid and forceful introduction of the vaccine came with unanticipated long-term negative effects (Dube et al., 2022; Goldenberg et al., 2023). Feeling forced into getting vaccinated without being able to deliberate and make their own informed decisions could lead people to lose trust in government and consequently reduce their willingness to comply with future policies and recommendations to get booster doses (Goldenberg et al., 2023). More longitudinal research investigating the unintended consequences of various public health interventions may provide insights for guiding future application and effectiveness. It is possible that for sustained uptake of protective behaviors, interventions that consider intrinsic motivations and thoughts (e.g., risk beliefs, vaccine efficacy confidence) as well as social factors (e.g., norms, altruism) may be most effective (Broomell & Chapman, 2021). This highlights the need to adjust the initial rollout of vaccination campaigns to focus on instilling confidence in vaccines, as well as balancing mandates with a sense of autonomy where people have space to make their own informed decisions without feeling forced to get vaccinated.

Overall, this research shows that individuals who are better able to delay gratification (i.e., opting for larger later rewards over smaller immediate rewards) are more likely to accept vaccine booster doses if they are recommended. The results suggest that successful promotion of long-term immunity may require greater emphasis on protecting health of the community, instilling trust in vaccines and government, increasing sense of autonomy when making decisions, and correcting biased risk perception and short-sighted thinking.

In Chapters 2, 3, and 4, we investigated the delay discounting as a predictor of vaccination and booster willingness. The results consistently show that steep delay discounting (i.e., one's tendency to favour smaller immediate rewards over larger later rewards) is associated with a reduced likelihood of being vaccinated, after controlling for demographic and mental health variables. In Chapter 5, we continue focusing on the dynamic process of deciding to get vaccinated. It is likely that individuals are on the continuum of baseline willingness to get vaccinated, ranging from those eagerly seeking vaccination at the earliest opportunity to those completely refusing the idea of vaccination. Interventions designed to increase vaccine uptake may need to be adjusted accordingly to meet individuals where they are in the process of deliberating their decision. In Chapter 5, we focus on individuals who expressed no intention to get vaccinated in 2021, and explore age × intolerance of uncertainty as predictors of changing their mind and getting vaccinated a year later. The effects of these variables are examined after controlling for other well-established factors, such as delay discounting and trust in science.

Chapter 5: Predictors of Change in Vaccination Decisions among Vaccine-Hesitant: Examining the Roles of Age and Intolerance of Uncertainty

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Widespread vaccination has been critical for containing the COVID-19 pandemic (Lopez et al., 2021) as well as other infectious diseases (WHO, 2020), but efforts have been threatened by vaccine hesitancy and resistance (Campos-Mercade et al., 2021; Szilagyi et al., 2021). Research on predictors of COVID-19 vaccination has considered effects of various factors, including environmental (e.g., government regulations and COVID-19 impact severity; Levitt et al., 2022) and individual factors (e.g., demographic variables; Choi et al., 2022). At the individual level, both immutable variables (e.g., demographic and personality variables; Choi et al., 2022; Jantzen et al., 2022; Li, 2022; Steinmetz, 2022) and potentially modifiable variables, including psychological (e.g., anxiety, depression; Pandolfo et al., 2022) and cognitive mechanisms (e.g., trust in science, delay discounting; Carrieri et al., 2023; Halilova et al., 2022) have been considered. Although the intention-behavior relationship has not been empirically demonstrated for all of the PHMs recommended during the pandemic (Liang et al., 2022), research shows that most individuals tend to follow through on their vaccination intentions (Strickland et al., 2022). In the evolving landscape of the pandemic, where protective behaviors transition from mandates to personal choices, it is crucial to identify the factors contributing to attitudes, intentions, and behaviors towards vaccines and boosters, especially in vaccine-hesitant individuals. The current longitudinal study investigated whether two factors known to influence health intentions and behaviors—intolerance of uncertainty and age—predicted decisions to be vaccinated in adults who were initially vaccine-hesitant. Understanding the factors contributing to how adults change their minds about vaccination during a pandemic is crucial for supporting a safe return to everyday life.

The pandemic increased uncertainty in many aspects of life. The sudden and widespread outbreak of COVID-19 caused global disruptions affecting healthcare, employment, education, and social interactions. The rapidly changing nature of the virus (El-Shabasy et al., 2022) and the subsequent implementation of various containment measures such as lockdowns and travel restrictions, created a sense of unpredictability and ambiguity (e.g., Capurro et al., 2021; Koffman et al., 2020; Zhao et al., 2022). Constantly evolving information, conflicting reports, and misinformation surrounding the efficacy of preventive measures further contributed to the uncertainty experienced by individuals and communities worldwide (Baerg & Bruchmann, 2022). Intolerance of uncertainty is a cognitive bias marked by a fear of, and reduced ability to handle, the unknown (Carleton, 2016). It is also an important factor in the process of behavior change when it comes to overcoming vaccine hesitancy. Interestingly, intolerance of uncertainty is associated with two potential outcomes with respect to vaccination. One strategy to manage uncertainty is to reduce or eliminate the source of the uncertainty. There is evidence that higher intolerance of uncertainty is associated with a higher likelihood of engaging in public health measures as a strategy to mitigate fears of the virus itself (Baerg & Bruchmann, 2022). An intolerance for uncertainty is also associated with a tendency to engage in coping behaviors, such as checking, repeating, and excessively preparing, with the intention to enhance one's perceived control over a given situation and reduce anxiety (e.g., Boswell et al., 2013; Jessup et al., 2022).

To the contrary, others have reported that those with higher intolerance of uncertainty are less likely to get vaccinated, due to heightened concerns about unknown risks and uncertain efficacy of the vaccine (Fitzgerald et al., 2022). Lower tolerance of ambiguity, defined as a sub-type of intolerance of uncertainty, is associated with vaccine hesitancy, again likely because of uncertainty around efficacy (Gillman et al., 2023). This phenomenon, known as "uncertainty paralysis" (Horenstein et al., 2019), represents another type of coping behavior—avoidance — that has been well-researched in relation to worry and anxiety (e.g., Ball & Gunaydin, 2022). Such behavioral avoidance is associated with cognitive inflexibility during times of increased uncertainty (Godara et al., 2023).

The factors that determine whether someone with high intolerance of uncertainty is more likely to engage in vaccination in an effort to reduce uncertainty, or instead become paralyzed and remain unvaccinated, remain unclear. Age may be critical to understanding the relation of intolerance of uncertainty to vaccination decisions under these circumstances. Although younger adults generally show more resistance to vaccination than older adults (Rebertson et al., 2021), and vaccination rates are lower amongst younger adults (Guay et al., 2021), there is also evidence that younger adults tend to be more open (Ferrini et al., 1994) and more encouraged by healthcare providers (Tucker et al., 2004) to change their health-related behaviours. Moreover, when faced with emotionally salient situations, a younger age is associated with increased use of problem-solving strategies to regulate emotions by managing or eliminating the stressor itself (Chen et al., 2018). Taken together, we hypothesize that unvaccinated individuals of younger age with high intolerance of uncertainty would be more likely to decide to get vaccinated compared to individuals of older age with high intolerance of uncertainty as a means to reduce or eliminate their experience of COVID-related uncertainty. However, age will not be associated with the likelihood of vaccination among individuals with low intolerance of uncertainty.

When faced with emotionally salient situations, older age is associated with increased use of passive or avoidant-denial coping strategies (Blanchard-Fields et al., 1995). Coupled with less flexibility in the selection of coping strategies (Eldesouky & English, 2018), it is likely that, as one gets older, higher intolerance of uncertainty becomes increasingly associated with an avoidant response such as uncertainty paralysis. Therefore, we predict that with increasing age, unvaccinated individuals with higher intolerance of uncertainty would be less likely to decide to become vaccinated.

In the current study, we examined data from a large longitudinal study, focusing on an adult sample of individuals aged 18 to 69 who reported being unvaccinated against SARS-CoV-2 in mid-2021. We investigated whether they had changed their mind a year later and were vaccinated, and whether intolerance of uncertainty and age measured at Time 1 interacted to predict change in vaccination status over time. In these analyses, we controlled for two variables related to vaccination decisions: delay discounting (Halilova et al., 2022; Hudson et al., 2022) and trust in science (Carrieri et al., 2023).

Method

Our methods and results are reported following the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement for cross-sectional studies (von Elm et al., 2007). This study is exploratory in nature. We aim to investigate and gain a preliminary understanding of factors contributing to the process of changing mind about vaccination among vaccine hesitant individuals. The exploratory design allows us to gather initial insights and generate hypotheses for further investigation.

Participants

Participants were recruited to participate in a larger study through an online platform (Prolific.co). At *Time 1* (between July and August, 2021), we aimed to recruit as many participants as possible to ensure a large enough sample of participants who might remain unvaccinated over time. The final *Time 1* sample comprised 6,926 participants from 13 countries[6]; n = 2,890 indicated that they were fully vaccinated, 1,465 that they were partially vaccinated, 2,012 that they were not vaccinated yet but were planning to get vaccinated in the future, and 559 that they were unvaccinated and did not intend to get vaccinated in the future.

At *Time 2*, approximately one year later (between July and August, 2022), all participants in the final sample of the larger study were invited to complete a follow-up survey. Of the 3,185 who participated a year later, a subset of individuals (n = 251) had indicated at *Time 1* that they had no intention to get vaccinated in the future. Of this sub-sample, 38% reported being vaccinated at *Time 2*.

Participants provided demographic information at *Time 1.* For the sub-sample reported here, the mean age was 31.93 years old (*SD* = 10.60); 127 self-identified as female, and 124 as male. Approximately 24% of the sample were residing in the US, 15% in Poland, 9% in the UK, 8% in Italy, 7% in Canada, 7% in Australia, 6% in Spain, 5% in France, 5% in Mexico, 4% in Germany, 4% in New Zealand, 4% in Portugal, and 1% in the Netherlands. Given the internationality of our sample, we used a subjective measure of relative income where participants estimated their current income relative to others in their own country/region on a sliding scale (0 = low, 50 = average, 100 = high; Adler et al., 2000; Smith et al., 2019). Average subjective relative income was 37.88 (*SD* = 21.10). Approximately 20% of our sample self-identified as essential workers in occupations supplying critical services during the pandemic: government; health and safety (e.g., healthcare, emergency response); utilities (e.g., water, energy, sanitation, transport, communications); food (e.g., supermarkets); and manufacturing. In terms of the highest level of education, 38% of the sample reported having a high school education, 47% a university degree (undergraduate degree or professional equivalent), and 15% a postgraduate degree.

Measures

Intolerance of Uncertainty Scale-12 (IUS-12; Carleton et al., 2007)

The IUS-12 is a 12-item measure of one's difficulties tolerating uncertainty (e.g., "I always want to know what the future has in store for me"). Participants provided responses to items on a 5-point scale (1 = Not at all characteristic of me; 5 = Entirely characteristic of me). The *intolerance of uncertainty* score was the sum of participants' responses to the 12 items, ranging from 12 to

[6] For a detailed description of the sample at Time 1, see Chapter 3.

60; the average score was 34.27 (*SD* = 9.61). The IUS-12 has been validated with clinical and non-clinical populations (e.g., Vadivel et al., 2022; Wilson et al., 2020). The scale showed acceptable internal consistency (m = 0.84). A detailed description of the factor analysis and estimation of internal consistency are provided in Appendix A.

Vaccination Status

Participants were asked to indicate their vaccination status at both *Time 1* and *Time 2*. Participants chose between 5 options: 1 = yes, I have received all necessary doses; 2 = yes, although I require another dose; 3 = no, but I am planning to get vaccinated; 4 = no, I am not planning to get vaccinated; 5 = prefer not to say. As described earlier, only participants with a *Time 1* response of 4 (“no, I am not planning to get vaccinated”) were included in this study. From their responses to this question at *Time 2*, a binary *vaccination status* variable was created as the primary outcome variable, distinguishing between those who were vaccinated (fully or partially) or not (including both those who were planning and not planning to get vaccinated in the future).

Reasons for Vaccination

At *Time 2*, participants had the opportunity to explain their reason(s) for their decision to be vaccinated or not. Participant responses were scored according to the primary reason described. To this end, we first examined the full corpus of responses in the larger study to identify the main reasons mentioned by participants. Reasons for getting vaccinated (or not) were: (1) ending the pandemic (e.g., “it will stop the virus”), (2) protecting oneself or others from COVID-19 (e.g., “to protect myself and my family”), (3) (non-) necessity (e.g., “I had to in order to continue being enrolled in college”), (4) trust (in science, government, or vaccines; e.g., “don’t trust the vaccine”), (5) vaccine availability, (6) health reasons (e.g., “medical complications”, “side effects”), or (7) other (e.g., “afraid of needles”). These categories were then used to classify each participant response provided by the current sub-sample; if multiple reasons were mentioned, the most prominent reason was scored. To establish the inter-rater reliability of this classification, the lead rater (S.F.C.) and two additional raters (W.F. and R.T.) independently classified 100 responses randomly selected from the larger study. Raters had 84-86% agreement on their categorizations of responses, and acceptable inter-rater reliability (Cohen’s Kappa ranged from = .79 - .81). S.F.C. then scored all of the responses from the participants reported on in this paper.

Trust in Science

We used two items designed to measure trust in scientific institutions by asking participants to indicate their confidence in science and in scientists on a scale from 0 = "no confidence at all" to 10 = “a lot of confidence” (Achterberg et al., 2017). The two items strongly correlated with each other ($r = 0.65$) and were added together into a single composite *Trust in Science* variable.

Delay Discounting

In this intertemporal choice procedure (Ciaramelli et al., 2021; Halilova et al., 2022; Mok et al., 2020), participants viewed pairs of monetary amounts and were asked to choose between smaller, immediate rewards which varied between trials, and a larger, delayed reward of $2,000. Participants were asked to make six choices at each of seven delays for the larger reward (waiting 1 week, 1 month, 3 months, 6 months, 1 year, 3 years, and 10 years before receiving the $2000 reward). An iterative, adjusting-amount procedure was used in which the amount of the immediate reward was increased or decreased based on the participant’s previous choice at that delay, converging on the amount of the immediate reward equivalent in subjective value to the delayed reward. Degree of discounting was measured by examining the subjective values of reward across the seven delays and computing *Area-under-the-Curve* (AuC), a single, theoretically-neutral measure of discounting (Myerson et al., 2001). The scores range from 0 to 1, with lower AuC representing a greater discounting rate (i.e., greater tendency to choose smaller immediate rewards over larger later rewards).

Attention Checks

To identify random responders, three items from the Conscientious Responder Scale (Marjanovic et al., 2014) were included at select points within the survey at *Time 1* (e.g., “To answer this question, please choose option three, neither agree nor disagree”). At *Time 2,* only one item was used given that the survey was much shorter. None of the participants in the current subsample failed the attention check.

Procedure

Data were collected longitudinally using two online Qualtrics surveys as part of a larger study. At *Time 1*, participants provided informed consent and, among other measures[7], provided

[7] For descriptions of other measures completed by the participants at *Time 1*, see Chapters 2 and 3

demographic information (including age and country of residence), completed the IUS-12 (Carleton et al., 2007) and the delay discounting task, and answered questions about their COVID-19 vaccination status. At *Time 2*, participants completed a series of COVID-related questions, including vaccination status and their reasons for their vaccination decision, as well as questions regarding their trust in science.

Results

Vaccination Status

A multilevel logistic regression model was constructed using R packages *lme4* (Bates et al., 2012) and *lmerTest* (Kuznetsova et al., 2017), with vaccination status at *Time 2* (unvaccinated vs. vaccinated) as the outcome variable, age (*Time 1*), IUS-12 (*Time 1*), and the age × IUS-12 interaction as predictors. Each participant's vaccination status at *Time 2* (Level 1) was nested within country (Level 2) to account for possible systematic differences across countries. There was an age × IUS-12 interaction on the likelihood of change in vaccination status, $b = -0.06$, $SE = 0.02$, $z = -3.00$, $OR = 0.95$, $p = .003$, 95% CI [0.91, 0.98]. The model was then expanded to include AuC (*Time 1*) and Trust in Science (*Time 2*) as predictors to control for the effects of these variables. A likelihood ratio test showed that a model including age × IUS-12 interaction accounted for more variance in the data compared to an intercept-only model, with only AuC and Trust in Science as predictors, $\chi^2(3) = 16.91$, $p < .001$. There was an age × IUS-12 interaction on the likelihood of change in vaccination status a year after expressing no intention of getting vaccinated (Figure 5.1), even after controlling for the effects of AuC and Trust in Science (Table 5.1). Specifically, the younger the age of the participant, the higher the odds of change in vaccination status a year later with high intolerance of uncertainty, $OR = 1.05$, $p = .006$. Controlling for age, high intolerance of uncertainty was associated with increased odds of being vaccinated, $OR = 7.34$, $p < .001$. Similarly, controlling for intolerance of uncertainty, younger age was associated with increased odds of being vaccinated a year after reporting no intention to get vaccinated, $OR = 1.05$, $p = .006$.

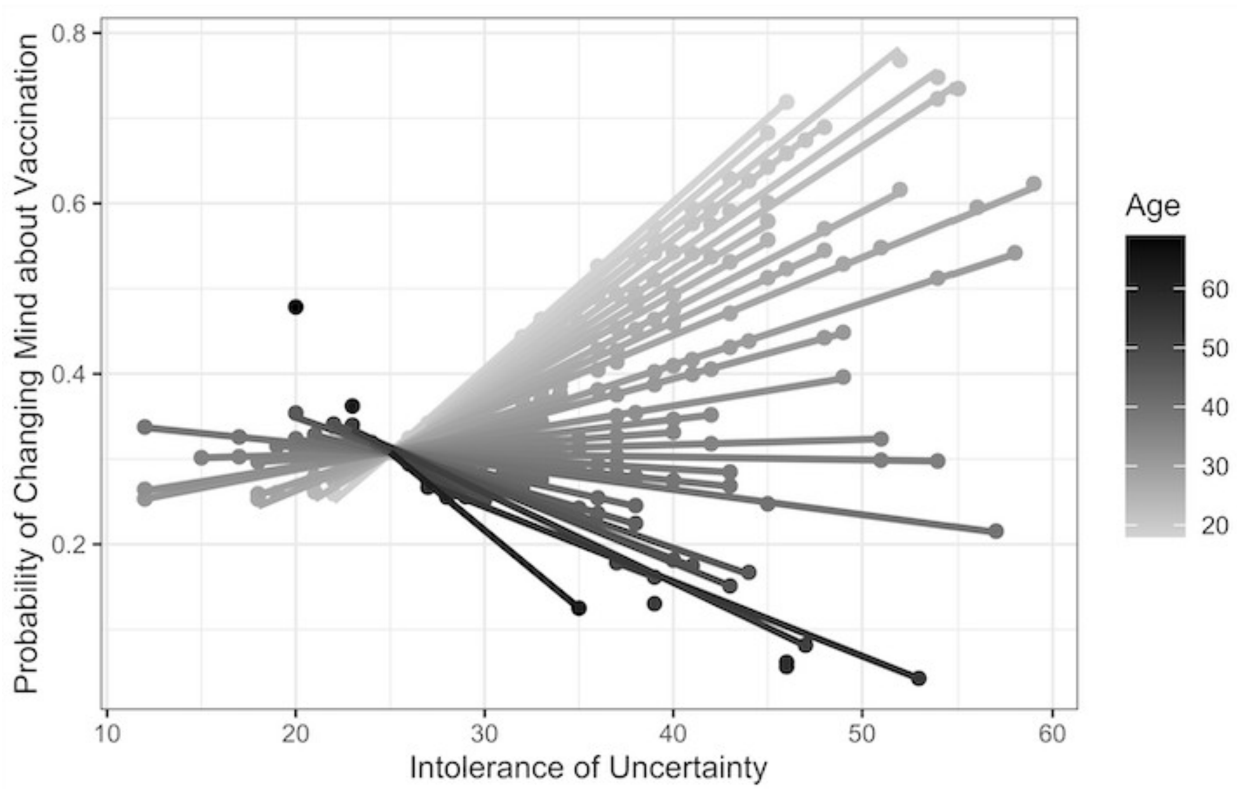
Table 5.1 Results of the Logistic Multilevel Model Predicting the Likelihood of Change in Vaccination Status a Year After Initially Expressing No Intention to Get Vaccinated

Fixed Effects	*b*	*SE*	*z*	*p*	*OR*	95% CI
Intercept	-0.27	0.92	-0.29	.774	0.77	[0.13, 4.68]
Trust in Science	0.13	0.04	3.30	<.001	1.14	[1.05, 1.22]
AuC	-0.26	0.63	-0.41	.683	0.77	[0.23, 2.65]
Age	-0.05	0.02	-2.72	.006	0.95	[0.92, 0.99]
IUS-12	1.89	0.63	3.01	.003	6.60	[1.93, 22.57]
Age x IUS-12	-0.05	0.02	-2.73	.006	0.95	[0.91, 0.99]
Random Effects	Estimate	*SD*				
Intercept error variance (country)	0.75	0.87				

Note. Age, IUS, and AuC were measured at *Time 1*. Trust in Science and vaccination status (the outcome variable) were measured at *Time 2*. Age is measured in years. IUS-12 = Intolerance of Uncertainty-12 total score; AuC = Area under the Curve; CI = Confidence interval; *OR* = odds ratio; *SD* = standard deviation; *SE* = standard error of the mean.

We also explored the effects of the predictors that were not a primary focus in our hypotheses: Trust in Science and delay discounting (AuC). After controlling for the effects of intolerance of uncertainty, age, and AuC, greater Trust in Science predicted an increased likelihood of getting vaccinated, $OR = 1.14$, $p < .001$. After controlling for the effects of intolerance of uncertainty, age, and Trust in Science, AuC was not a significant predictor of vaccination, $OR = 0.77$, $p = .683$.

Figure 5.1 The Likelihood of Being Vaccinated at Time 2, a Year after Reporting No Intention to Get Vaccinated



Note. The likelihood of being vaccinated (0 = unvaccinated, 1 = vaccinated) at *Time 2*, a year after reporting no intention to get vaccinated, plotted by age and total score on the Intolerance of Uncertainty Scale at *Time 1*. The plot indicates that younger age (shown in lighter shades) is associated with greater likelihood of change in vaccination status a year later in individuals with higher intolerance of uncertainty.

Vaccination Reasons

At *Time 2*, participants could provide reasons for their decision to become vaccinated or not. Of the 95 participants who changed their mind about vaccination one year later, $n = 49$ provided reasons for their decision: 45% felt it necessary to get vaccinated (8% for social reasons, 18% for work, and 18% for other reasons), of which 95% explicitly mentioned the influence of government mandates; 29% sought protection against the virus (16% for themselves, 10% for their family, 2% for others), of which 21% specifically mentioned preventing severe illness or death; 8% based their decision on trust in vaccines and 2% trust in science; 2% were influenced by vaccine availability; 2% had a desire to contribute to ending the pandemic; and 12% were scored as other (e.g., peer pressure). Out of 157 participants who did not change their mind and remained unvaccinated a year later, $n = 109$ provided reasons for their decision: 43% based their decision on mistrust (24% in vaccines, 10% in government, 5% in science, 5% other); 31% said vaccination was not necessary for them; and 16% said they were protecting themselves from experiencing other health complications or side effects; and 10% mentioned “other” reasons for remaining unvaccinated, referring primarily to personal circumstances (e.g., “afraid of needles”) or personal opinions (e.g., “don’t like vaccines”).

Discussion

This longitudinal investigation assessed the contributions of age and intolerance of uncertainty to the process of changing one’s mind about getting vaccinated a year after reporting no intention to get vaccinated, over and above well-established predictors of vaccination, such as delay discounting and trust in science. We found that intolerance of uncertainty interacted with age to predict the likelihood of changing one’s mind about vaccination. With younger age, those who were more intolerant of uncertainty in 2021 were more likely to be vaccinated in 2022. Thus, although younger adults may have shown greater resistance to vaccination throughout the pandemic (Pires, 2022), our findings suggest that younger adults with high intolerance of uncertainty were more likely to change their minds about vaccination over the course of a year.

These findings build on extant literature emphasizing the role of intolerance of uncertainty in health behaviours, such as vaccination. Intolerance of uncertainty is commonly associated with behavioral avoidance of situations that are uncertain. In the context of COVID-19, however, exposure to uncertainty was unavoidable, given the rapidly changing situation in terms of the threat of the virus (e.g., waves of infection, new variants) and changing policies and mandates. In those who experience higher levels of anxiety when encountering uncertainty (i.e., those highly intolerant of uncertainty), younger age was associated with an increased likelihood of changing one’s mind. This finding is broadly consistent with previous work showing that younger adults have more flexible coping styles (Blanchard-Fields et al., 1995; Eldesouky & English, 2018) and are more likely to take action—in this case, getting vaccinated—as a means to eliminate stressors (Chen et al., 2018). The findings are also consistent with previous research indicating a functional role of anxiety in health-related behaviors, showing that decisions to not get vaccinated are associated with a decrease in fear of COVID-19 (Mertens et al., 2022).

Among those participants who changed their vaccination status a year after stating no intention to get vaccinated, the most commonly provided reason for doing so (approximately 45%) was because of government mandates related to work and social activities; the second most common reason (29%) was related to prevention of serious illness. Even though all of these participants were vaccinated at *Time 2,* these different catalysts may reflect different forms of behavior change. On the one hand, individuals who described getting vaccinated because they were mandated to do so might have changed their behavior (i.e., became vaccinated) without changing their mind about vaccination (e.g., "I was planning to travel abroad so needed to be fully vaccinated. Otherwise I wouldn't have gotten the vaccines"). These individuals may be less likely to engage in protective behaviors voluntarily, which is important now that the pandemic is over and responsibility for maintaining long-term immunity shifted from government mandates to individual choices. On the other hand, individuals who stated that they got vaccinated to protect themselves against severe illness may be more likely to receive future doses for long-term immunity maintenance because of the apparent change in their belief about vaccination. Future research should focus on investigating the long-term maintenance of behavior change and how to combine short- and long-term interventions to influence both rapid and sustained uptake of protective health behaviors.

Older age was associated with a lower likelihood of changing one's mind about vaccination, particularly among those who endorsed higher IU. This finding is consistent with research on uncertainty paralysis (i.e., inaction in the face of uncertainty about the outcome), both in relation to COVID-19 protective behaviors (Fitzgerald et al., 2022) and other health-related issues (e.g., Berenbaum et al., 2008; Piccolo et al., 2019). Our results suggest that uncertainty paralysis may be a more prevalent response among individuals of older age when coping with uncertain situations, and may reflect the adoption of avoidant coping strategies (Blanchard-Fields et al., 1995). The findings are also consistent with previous research showing that as adults age, they tend to become less flexible, are more resistant to change, and display an increased preference for stability and familiarity (Matamales et al., 2016). This highlights the importance of targeted communication strategies, suggesting that approaching individuals of older age with messages that instill certainty (e.g., clear content from a trusted source, like a family doctor; Salali & Uysal, 2023) may be more effective in changing their mind about vaccination. Other intervention approaches may also involve psychoeducation and behavioral approaches (e.g., exposure; Freeman et al., 2021) focused on introducing strategies to reduce IU.

Another explanation for the moderating effect of age on the relationship between IU and changing one's mind about vaccination is the age differences in beliefs about uncertainty and worry. IU diminishes as people transition from young adulthood to middle and advanced age, as they learn that excessive worrying about the unknown is counterproductive and as their belief in the functional value of worry weakens (Basevitz et al., 2008). It is possible that, compared to their older counterparts, younger individuals were more motivated to get vaccinated and reduce feelings of uncertainty because they experienced more worries about potential consequences of not getting vaccinated. This possibility is consistent with research showing that age moderates the relationship between COVID-19 worries and anxiety. Among individuals aged 50+ years, anxiety was unrelated to perceived likelihood of contracting COVID-19, whereas among younger ages (18-49 years), these variables were positively correlated (Wilson et al., 2020).

It is notable that the interaction between IU and age accounted for a significant amount of variance in likelihood of change in vaccination status, over and above other well-established cognitive predictors of vaccination, such as trust in science (e.g., Carrieri et al., 2023) and delay discounting (e.g., Halilova et al., 2022; Hudson et al., 2022). These findings are supported by participants' qualitative reasons for their decisions, which revealed evidence of mistrust in science (e.g., "COVID vaccine is ineffective"), delay discounting (e.g., "I don't think the benefits outweighed the long-term unknown and known short-term risks"), as well as uncertainty (e.g., "I'm just worried about how my body will handle it. I mostly trust the vaccine, just not for myself."; "I needed it to travel, but I'm not sure about it so I won't get the third dose.").

The range of qualitative responses confirm the complexity of the decision-making process when it comes to getting vaccinated. It is possible that more effective interventions for encouraging people to engage in protective behaviors would have to carefully assess their stage of readiness for change (Prochaska & DiClemente, 1983). For example, individuals in the *preparation* stage (i.e., have decided to change and are planning to take the first steps) may benefit from interventions involving individual nudges (e.g., Dai et al., 2021; Milkman et al., 2021). In our sample, one participant stated "I've been too busy" as their reason for not getting vaccinated. It is possible that someone who is generally not opposed to vaccines but is struggling to find time to follow through on their intentions may respond well to nudges to get vaccinated through personal messages. However, the same intervention may not be effective for individuals in the *precontemplation* stage (i.e., not yet considering change), as was evident from a study showing ineffectiveness of nudges in a vaccine-hesitant population (de Riddler et al., 2023). A number of participants in our sample who expressed concerns about vaccines (e.g., "I don't trust that it will not adversely affect me") may not be as receptive to the nudge messages. Incorporating alternative interventions (e.g., motivational interviewing; Miller & Rollnick, 2013) for the individuals in the precontemplation stage may be necessary to facilitate change.

The choice of intervention should also consider the context. When a rapid change in behavior is required for short-term virus containment, government mandates seem to be the most effective, as suggested by participants' qualitative responses (e.g., "I needed the vaccine for employment") and supported by prior research (Brewer et al., 2018; Broomell & Chapman, 2021). The pervasive uncertainty associated with the pandemic, reflected in government policies (e.g., lack of a clear timeline for easing restrictions, ambiguity about future travel and social activity constraints), may motivate individuals to take action and get vaccinated. Conversely, if the objective is to promote long-term immunity maintenance (e.g., increasing willingness to receive vaccine booster doses), it will be essential to concentrate on programs aimed at changing people's attitudes in the long run, rather than immediately altering their behavior.

Overall, this study showed an interaction between age and IU on the decision to get vaccinated a year after initially expressing no intention to do so, over and above the effects of delay discounting and trust in science. In the context of this research, we also explored participants' own reasoning about their vaccination decisions. Future research could further examine various factors of people's uncertainty regarding vaccination. Unlike studies investigating predictors of vaccination during COVID-19 at a single time point, this longitudinal investigation of the process of changing one's mind about vaccination in vaccine-hesitant populations allows for a better understanding of the dynamic nature of vaccine hesitancy and when it might shift into vaccine willingness. By recognizing the influence of age and IU on changes in vaccine decisions, public health campaigns can tailor their messages to address specific concerns and uncertainties (e.g., trust in science vs. uncertainty about future mandates) in different age groups. Additionally, future longitudinal research will inform development of targeted interventions aimed at reducing vaccine hesitancy over time, emphasizing the importance of building trust in vaccines and healthcare systems. Recognizing the complex interplay between age, uncertainty, and vaccination decisions can contribute to more effective strategies to promote vaccine uptake and ultimately inform public health measures in preparation for future pandemics or other health crises.

Chapter 6: General Discussion

The research described in this dissertation investigated the utility of cognitive biases, delay discounting, and intolerance of uncertainty in predicting compliance with public health measures during the pandemic. The data were collected longitudinally across two time points, between June and August, 2021 (*Time 1*) and between July and August, 2022 (*Time 2*), from participants in 13 countries across North America, Europe, and Australasia. In Chapter 2, individuals who tended to choose larger later rewards over smaller immediate rewards (i.e., less future discounting) were more likely to be vaccinated, after controlling for demographic variables and distress. Chapter 3 reproduced the results of Chapter 2, based on a larger sample of participants. Furthermore, in this chapter delay discounting predicted adherence to other PHMs, including cleaning and physical distancing. However, the association was the opposite as for vaccination status: individuals who favoured smaller immediate rewards over larger later rewards (i.e., more future discounting) engaged in more cleaning and physical distancing. Delay discounting was not a predictor of mask-wearing. In Chapter 4, individuals who chose larger later rewards over smaller immediate rewards (i.e., less future discounting) were more likely to be express willingness to receive a booster dose. In Chapter 5, the focus was on individuals who reported no intention to get vaccinated at Time 1. Intolerance of uncertainty interacted with age to predict the likelihood of changing one's mind and being vaccinated at Time 2. Specifically, individuals who were highly intolerant of uncertainty were more likely to be vaccinated a year later compared to those who are low in intolerance of uncertainty. This association was stronger among younger individual compared to their older counterparts.

The current findings have important implications across several areas, including: (1) contributions to our understanding of vaccine hesitancy; (2) contributions to understanding delay discounting and health-related decision-making more broadly; and (3) informing future public health interventions. These implications will be discussed, along with limitations of the research reported here, and attempts by other researchers to address the pandemic and its consequences.

Theoretical Models of Vaccination

Several theoretical models have been proposed to offer a deeper understanding of vaccination decisions. The 3C Model of vaccination proposed by the WHO's Strategic Advisory Group of Experts (SAGE) on Immunization in 2012 (as described in Larson et al., 2014) explains vaccine hesitancy by focusing on 3 factors: *complacency* (i.e., perception of low risk of infection, leading to underestimation of the importance of vaccination), *convenience* (i.e., ease of access), and *confidence* (i.e., trust and belief in vaccines, healthcare providers, and the vaccination process). The findings in Chapters 2, 3, and 4 reveal that individuals with steeper delay discounting tendencies may prioritize immediate concerns (e.g., potential side effects) over the long-term benefits of vaccination, potentially explaining why some individuals perceive low disease risk and, consequently, feel complacent about vaccination. Additionally, trust and belief in vaccines were mentioned by participants (Chapters 4 and 5), representing the confidence factor of the 3C model. The 5C Model of vaccination (Betsch et al., 2018) extends the 3C model by adding *collective responsibility* (i.e., desire to receive a vaccination with the goal of protecting others) and *risk calculation* (i.e., weighing individual health risks of infection versus those of being vaccinated). Considering the complex interplay between individual health risks associated with infection and potential vaccine side effects, the risk calculation factor becomes particularly relevant for vaccination decisions. Intolerance of uncertainty is a cognitive bias that may influence risk perception (e.g., Graffeo et al., 2022). Encountering situations with uncertain outcomes (e.g., rapidly changing government mandates during the pandemic) may be perceived as riskier by those who are intolerant of uncertainty than by those who are more comfortable with uncertainty. In other words, the mere presence of uncertainty may inflate risk calculation in individuals with high intolerance of uncertainty. Delay discounting is another cognitive factor that may potentially influence this risk calculation.

There are delay discounting theories that consider delay as a form of inherent risk (e.g., Bixter & Luhmann, 2015; Green & Myerson, 1996; Keren & Roelofsma, 1995). These *delay-as-risk* theories view delay as a measure of risk-aversion, noting that the longer individuals must wait for a reward, the more uncertain, unpredictable, and thereby riskier their future becomes. Delay can introduce various unpredictable factors, such as changes in circumstances, external events, or unforeseen challenges. Individuals with steeper delay discounting tendencies may be more risk-averse when considering potential vaccine side effects, leading to biased risk calculations.

Health-Related Decision-Making

Delay discounting has been previously considered as a predictor of health-related behaviors, such as alcohol use (e.g., Yi et al., 2010), smoking (e.g., Stein et al., 2016), and binge-eating (e.g., Steward et al., 2017), such that those who discount the future more are more likely to engage in behaviours detrimental to their health. The current findings extend this work to the context of compliance with PHMs. Much of the previous research on predictors of compliance with PHMs relied on expectancy-value theories (e.g., Limbu et al., 2022; Ohnmacht et al., 2022; Wollast et al., 2021). Expectancy-value theories, such as Theory of Planned Behavior (Ajzen, 1991) and the Health Belief Model (Rosenstock, 1966), posit that one's decisions are influenced by their expectations of outcomes and the subjective value of these outcomes, guiding choices based on perceived costs and benefits. According to these theories, simply providing individuals with more information about costs and benefits should lead to changes in the health-related decisions. However, these theories do not account for cognitive biases and heuristics in human decision-making. In contrast, dual-process theories acknowledge the existence of two distinct systems for decision-making, recognizing that a more automatic, heuristic-driven system (System 1) often guides our choices before the more deliberate and analytical system (System 2) is engaged (Kahneman & Tversky, 1979). Delay discounting is an example of a System 1 bias observed in human decision-making (Miller et al., 2014). The negative association between delay discounting and vaccination reported in Chapters 2 and 3, suggests that interventions focused on correcting delay discounting may help people arrive at the decision to get vaccinated, one that is optimal for their long-term health. Simply providing people with more information may not be sufficient to encourage people to get vaccinated.

Furthermore, the findings from Chapter 3 also show a positive relationship between delay discounting and other PHMs, including physical distancing and cleaning behaviors. Traditionally, delay discounting has been perceived as a cognitive “flaw” in decision-making that requires correction (Odum, 2011). However, the current findings suggest that with respect to certain health behaviors (e.g., the decision to wash one’s hands and/or to avoid crowded places), prioritizing immediate rewards (e.g., feeling more protected in the moment) may lead to health benefits. These findings encourage a more nuanced approach to understanding the cognitive processes involved in a broader range of health-related decision-making.

Overall, the current findings underscore the utility of behavioral economic measures in improving our understanding of health-related decisions, particularly those pertaining to compliance with PHMs. This research encourages the use of behavioral economic measures as tools for empirically exploring and informing public health research.

Public Health Interventions

Throughout the pandemic, government mandates have emerged as the primary mechanism for promoting compliance with PHMs. Although these mandates have been effective in increasing PHM compliance (Dube et al., 2022; Maquiling et al., 2023; Mahmoudi & Xiong, 2022; Mello et al., 2022; Talic et al., 2021), they have also raised concerns about potential long-term consequences, including a decline in trust in government (Bardosh et al., 2022; Dube et al., 2022; Goldenberg et al., 2023; Levitt et al., 2022; Mouter et al., 2022), promotion of stigma and social polarisation (Bardosh et al., 2022), reduced willingness to receive booster doses, and even hesitancy toward routine vaccines (Goldenberg et al., 2023). Such costly potential long-term consequences of government mandates (e.g., Graffigna et al., 2021 Schmelz, 2021) indicate a possible need for alternative intervention approaches that allow individuals to have more autonomy over their health-related decisions.

The association between delay discounting and vaccination status (Chapter 2,3, and 5) could inform the development of evidence-based public health policies and the design of targeted interventions to promote vaccine acceptance. One potential avenue for intervention involves providing individuals with concrete and immediate incentives for vaccination (e.g., gift cards, vouchers, or access to privileges), thereby accommodating people's tendency to discount future rewards. Indeed, offering financial incentives for vaccination resulted in increases in vaccination rates, albeit with small effect sizes (Khazanov et al., 2023; Mardi et al., 2022). However, this approach to intervention is costly to implement and does not lead to sustained changes in attitudes and behavior (Vlaev et al., 2019). Sustained attitude change is important when it comes to follow-up booster doses that are not mandated.

An alternative approach to intervention informed by the current research involves cueing individuals to think about personally relevant future events and making delayed rewards more salient. Multiple studies showed that encouraging individuals to imagine the future leads to a decrease in their discounting rate, increasing their tendency to favour larger later rewards over smaller immediate rewards (Bromberg et al., 2017; Ciaramelli et al., 2021; Daniel et al., 2013; Mok et al., 2020; O'Donnell et al., 2019; Peters and Büchel, 2010; Rung & Madden, 2018; Stein et al., 2016; Ye et al., 2022; Zhang et al., 2018). In the context of promoting vaccination, public health campaigns can focus on the long-term advantages of vaccination, such as protecting one's health and maintaining population immunity. Framing vaccination as an investment in personal and societal well-being could shift individuals' temporal perspective when deciding to get vaccinated. Future research should investigate the efficacy of inducing future imagining on compliance with PHMs, particularly the willingness to get vaccinated. This approach to intervention is particularly promising because it allows individuals the autonomy to deliberate and make their own decisions about their health, and in doing so, potentially leads to change in beliefs among the vaccine-hesitant, facilitating sustained immunity through booster doses.

The current research also highlights the importance of tailoring interventions to match individuals' readiness for change, aligning with the stages of change model (Prochaska & Velicer, 1997). It is possible that individuals in the pre-contemplation stage, who may not yet recognize the need for vaccination, are more likely to reconsider their stance when interventions address their intolerance of uncertainty. In contrast, those in the contemplation stage, who are actively considering vaccination, may benefit from interventions that prompt them to envision future events that are personally relevant and positive in nature. This would reinforce the benefits of engaging in vaccination. However, these findings indicate that this approach may not generalize across all PHMs. With respect to physical distancing and handwashing, for instance, the findings of Chapter 3 suggest that an intervention focusing on the here and now by emphasizing immediate and tangible benefits may prove most effective. These findings underscore the necessity of differentiating interventions based on the readiness for change and the specific health behaviors in question, with the aim of promoting widespread engagement in multiple PHMs.

Limitations and Future Directions

This research has several limitations, including generalizability of findings to other countries, other vaccines, and different pandemic contexts; reliance on self-report measures; the nature of longitudinal data (e.g., attrition); the correlational nature of the findings; and the evolving context of the pandemic itself. With respect to generalizability, even though we tested participants from 13 countries, it is unclear whether the findings would generalize to other parts of the world that are not represented in this research, including Asian, South Asian, and Latin American countries. It is possible that in collectivistic cultures, the association between delay discounting and PHM compliance is weaker than in individualistic cultures, and the benefit of a community is weighed higher than individual gains and losses. Future research should attempt to replicate these findings in other countries. Another potential limitation of this research is that participants were recruited online through a crowdsourcing platform. Therefore, the results may not be representative of communities without access to the internet. It would be important to replicate these findings in different regions, including Indigenous communities where the rate of infection spread is relatively high and the public health mandate options are relatively limited (Benji et el., 2021; Huyset et al., 2022). It would also be beneficial to try to replicate these findings in different contexts, including during the emergence of new strains of COVID-19 (e.g., EG.5), as well as other infectious diseases. It is possible that the association between delay discounting and PHM compliance may be attenuated by environmental factors, including number of cases and hospitalizations, media attention, government and institutional policies. Investigating compliance with PHMs during new strains on COVID-19 can further inform decision-making dynamics in long-term immunity maintenance.

The analyses presented in this research are correlational in nature, not allowing us to confirm a causal relationship between delay discounting and PHMs. It is possible that delay discounting causes compliance with PHMs. Alternatively, it is possible that delay discounting mediates the relationship between another variable (e.g., risk-aversion, self-control) and PHM compliance. Future research should focus on establishing a causal relationship between the variables by using an experimental design and randomly assigning participants to a *future imagining induction* or *control* conditions. Participants' subsequent compliance with PHMs could then be compared between the two groups.

Future research could also benefit from exploring discounting of delayed losses, which are generally discounted less steeply than rewards (e.g., Bailey et al., 2018). Additionally, it is possible that integrating discounting of losses with discounting of rewards could contribute to a better understanding of delay discounting overall. Another limitation of this research is that delay discounting was measured using a monetary paradigm. Future research would benefit from investigating the effects of non-monetary measures of delay discounting (e.g., social discounting; Jones & Rachlin, 2009) on PHMs to improve understanding of the association between the construct and the protective behaviors.

Lastly, the data were collected during a specific timeframe, between June and August 2021 and July and August 2022, a period characterized by dynamic changes in the COVID-19 pandemic. Variants of the virus emerged, vaccination campaigns evolved, and public perceptions and behaviors fluctuated in response to new information and guidelines. In the presence of these confounding factors, it is difficult to isolate the effects of any single variable on behavior during that time.

Conclusion

The studies reported in this dissertation investigated health-related decision-making, with a specific focus on vaccination and other PHMs during the pandemic. By examining the role of cognitive biases, delay discounting and intolerance of uncertainty, this research has provided valuable insights into the factors contributing to vaccine uptake and adherence to other PHMs. The findings have illuminated the complex interplay between cognitive biases and individual characteristics, offering a more comprehensive understanding of how people make choices regarding their health.

The current findings also emphasize the importance of using evidence-based public health policies. Although expectancy-value theories provide valuable insights into factors contributing to compliance with PHMs, they may not fully account for the cognitive biases and temporal preferences that shape health-related decisions. Integration of behavioral economic measures into predictive models, and awareness of dual-process theories of decision-making, enrich our comprehension of health-related choices and inform the development of tailored interventions. As the world continues to grapple with the challenges of vaccination during – and beyond – a pandemic, this research contributes to a broader conversation on how public health strategies can be enhanced to address vaccine hesitancy and promote vaccine acceptance in various populations. In addition to contributing to the theoretical frameworks of health-related decision-making, the current findings may also inform public health policies and interventions aimed at safeguarding global health.

Appendix A: IUS-12 Reliability Estimation

A group of participants (n = 6,926) recruited between June and August 2021 completed a measure of intolerance of uncertainty (IUS-12; Carleton et al., 2007) among other measures. Participants provided responses to the 12 items from 1 = *not at all characteristic of me* to 5 = *entirely characteristic of me*. Originally, the scale was developed as a two-factor measure of intolerance of uncertainty: prospective anxiety and inhibitory anxiety (Carleton et al., 2007). Subsequently, several studies evaluating psychometric properties of the scale determined that a bifactor model would fit the IUS data best (e.g., Lauriola et al., 2016; Wilson et al., 2020).

Confirmatory factor analysis (CFA) was used to estimate a model that fits the data best. Bivariate correlations between the scale item are generally moderate (r = .20 to .64), suggesting that one-factor model might not fit the data best. All of the CFA models presented below were fitted with maximum likelihood estimation with robust standard errors using MLR estimator in *lavaan* package (Rosseel, 2012) in R. Model fit was evaluated with the comparative fit index (CFI), the Tucker-Lewis Index (TLI), the standardized root mean squared (SRMR), and the root mean square error of approximation (RMSEA). The following rough guidelines were used in evaluating model fit: CFI and TLI values greater than .90-.95, SRMR lower than .08, and RMSEA of .05 or lower would indicate that a model fits the data well.

Three CFA models were considered, including the one-factor model, two-factor model, and the bifactor model. The results of the fit statistics are presented in Table A1. The bifactor model was estimated with intolerance of uncertainty as a general factor determining all 12 items, and two specific factors corresponding to prospective and inhibitory anxiety with their covariances set to 0. The model fit statistics indicate that the model fits the data well (see Table A1) and superior to the one-factor and two-factor models.

Table A1. Robust fit statistics for the Intolerance of Uncertainty Scale 12-item models

Model	χ^2	df	CFI	TLI	RMSEA	SRMR	$\Delta\chi^2$	Δdf
One-factor model	3872.10	54	0.69	0.84	0.110	0.062	-	-
Two-factor model	2939.80	53	0.90	0.88	0.096	0.057	932.2*	1
Bifactor model	106.87	42	0.95	0.92	0.078	0.046	2832.93*	11

*$p < .05$

Reliability Estimates for the Bifactor Model

The variability in factor loadings (0.12 – 0.77) suggests that the assumption of tau-equivalence is likely violated, and omega would be a better reliability estimate than alpha. Internal consistency index, omega, was obtained using reliability function of *psych()* package (Revelle, 2020). The omega-hierarchical for the general factor (.84) indicates that the scale provides an acceptably reliable measure of a general construct of intolerance of uncertainty.

Appendix B: Author Contributions

Study 1

Conceptualization: Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum ***Methodology***: Julia G. Halilova, Samuel Fynes-Clinton, Leonard Green, Joel Myerson, Donna Rose Addis, and R. Shayna Rosenbaum. ***Investigation:*** Julia G. Halilova, Samuel Fynes-Clinton, Kai Ruggeri, Donna Rose Addis, and R. Shayna Rosenbaum ***Visualization:*** Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum. ***Funding acquisition:*** Leonard Green, Joel Myerson, Jianhong Wu, Donna Rose Addis, and R. Shayna Rosenbaum. ***Project administration:*** Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum ***Data Analysis:*** Julia G. Halilova, Samuel Fynes-Clinton. ***Supervision:*** Donna Rose Addis, and R. Shayna Rosenbaum ***Writing - original draft:*** Julia G. Halilova, Donna Rose Addis, and R. Shayna Rosenbaum. ***Writing - review and editing***: Julia G. Halilova, Samuel Fynes-Clinton, Leonard Green, Joel Myerson, Jianhong Wu, Kai Ruggeri, Donna Rose Addis, and R. Shayna Rosenbaum.

Study 2

Conceptualization: Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum. ***Methodology***: Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum. ***Investigation:*** Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum. ***Visualization:*** Julia G. Halilova *Funding acquisition:* Donna Rose Addis and R. Shayna Rosenbaum. ***Project administration:*** Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum. ***Data Analysis:*** Julia G. Halilova. *Supervision:* Donna Rose Addis, and R. Shayna Rosenbaum. ***Writing - original draft:*** Julia G. Halilova, Donna Rose Addis, and R. Shayna Rosenbaum. ***Writing - review and editing***: Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum.

Study 3

Conceptualization: Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum. ***Methodology:*** Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum. ***Investigation:*** Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum. ***Visualization:*** Julia G. Halilova. ***Data Analysis:*** Julia G. Halilova. ***Qualitative Data Scoring:*** Samuel Fynes-Clinton and Caitlin Terrao ***Funding acquisition:*** Donna Rose Addis and R. Shayna Rosenbaum. ***Project administration:*** Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum ***Supervision:*** Donna Rose Addis, and R. Shayna Rosenbaum ***Writing - original draft:*** Julia G. Halilova, Caitlin Terrao, Donna Rose Addis, and R. Shayna Rosenbaum ***Writing - review and***

editing: Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum.

Study 4

Conceptualization: Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum. ***Methodology:*** Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum. ***Investigation:*** Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum. ***Visualization:*** Julia G. Halilova. ***Data Analysis:*** Julia G. Halilova. ***Qualitative Data Scoring:*** Samuel Fynes-Clinton and Caitlin Terrao ***Funding acquisition:*** Donna Rose Addis and R. Shayna Rosenbaum. ***Project administration:*** Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum ***Supervision:*** Donna Rose Addis, and R. Shayna Rosenbaum ***Writing - original draft:*** Julia G. Halilova, Donna Rose Addis, and R. Shayna Rosenbaum ***Writing - review and editing:*** Julia G. Halilova, Samuel Fynes-Clinton, Donna Rose Addis, and R. Shayna Rosenbaum.

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