How Humans Value Delayed Protection: Biological Vulnerability and Intertemporal Health Decisions

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Abstract

Vaccination timing critically determines how long individuals remain biologically exposed to infectious risk. This study quantifies intertemporal preferences for vaccination using a discrete choice experiment among 1,027 adults in Wuhan, China. Waiting time is embedded directly into vaccine attributes, enabling estimation of time-discount parameters and marginal willingness-to-accept (MWTA) for delayed protection. Results reveal pronounced present-oriented preferences: respondents strongly discount delayed vaccination, with hyperbolic parameter $\varkappa = 0.225$ and exponential $\delta = 0.160$. Delay aversion is heterogeneous—individuals with chronic medical conditions, lower institutional trust, and irregular preventive-health routines exhibit substantially steeper discounting and require greater compensation to tolerate waiting. These patterns suggest that biological vulnerability and uncertainty about future protection systematically shape intertemporal health investment. The findings demonstrate that vaccination delays impose regressive behavioural burdens, disproportionately affecting medically and socially vulnerable populations. By linking time preferences to biological risk and institutional context, this study advances understanding of inequalities in preventive health timing and highlights the importance of incorporating temporal behaviour into public health strategies.

Keywords: Vaccination timing; Intertemporal preferences; Health capital; Biological vulnerability; Institutional trust; Delay aversion; Discrete choice experiment

1. Introduction

Timely access to biological protection is a central determinant of human exposure to infectious disease and the preservation of health capital [7, 28]. While vaccination coverage is often treated as a binary outcome—vaccinated or not—the timing of vaccination critically shapes the duration for which individuals remain unprotected and biologically vulnerable. Even modest delays can extend periods of exposure and shift outbreak dynamics, making the intertemporal timing of uptake as critical as aggregate population coverage [26]. Delays in vaccination therefore prolong exposure to infection risk, during which individuals face potential health deterioration and uncertainty about future protection. Understanding how humans evaluate such delays is essential for explaining observed patterns of preventive health behaviour under infectious risk.

From an intertemporal perspective, vaccination timing represents a health investment decision in which immediate costs—such as effort, inconvenience, or perceived side effects—are traded off against delayed and uncertain biological benefits [9]. When protection is postponed, individuals must decide whether the future reduction in infection risk sufficiently compensates for remaining exposed in the present. These trade-offs are not uniform across populations. Institutional trust [17], perceived biological vulnerability [5], and stable preventive-health routines [18] shape how future protection is perceived and discounted, giving rise to systematic heterogeneity in tolerance for delayed protection. These determinants appear across diverse institutional settings, reflecting general features of intertemporal health decision-making.

A growing body of research documents that vaccination timing is influenced by behavioural factors such as impatience, risk perception, and institutional trust, alongside logistical access constraints [1, 27, 8]. However, much of this literature continues to treat waiting time as an administrative friction rather than as a biologically meaningful interval of continued exposure [21, 31]. From a physiological perspective, delay is not neutral: each additional period without protection entails ongoing exposure during which infection risk, potential morbidity, and uncertainty accumulate. Despite this, few discrete choice experiments have directly quantified how individuals value delayed protection as an intertemporal health trade-off [34, 10], and existing studies of health-related discounting have not linked sensitivity to delay to structural determinants such as institutional trust or chronic medical vulnerability [25]. Without explicitly measuring the behavioural cost of remaining

unprotected, it remains difficult to assess how delays in access translate into unequal, exposure-relevant health burdens across populations or to design time-consistent interventions that account for heterogeneous experiences of waiting.

To address these gaps, this study examines how individuals value the *timing* of vaccination as an intertemporal health investment. We use a discrete choice experiment (DCE) administered to 1,027 adults in Wuhan, China, in which waiting time is embedded directly into vaccine attributes. This design allows us to recover formal time-preference parameters that characterize sensitivity to delayed biological protection. Rather than treating waiting as a purely logistical friction, we conceptualize delay as a biologically meaningful interval during which individuals remain exposed to infection risk and potential health damage. From this perspective, vaccination timing reflects how individuals trade off immediate burdens against the expected preservation of future health under uncertainty.

Wuhan provides a particularly informative empirical setting for studying these processes. As a city with high population density, early pandemic exposure, and strong public-health visibility, Wuhan constitutes a high-salience environment in which the biological consequences of delayed protection are readily understood by respondents. This salience sharpens the behavioral signal linking perceived vulnerability, trust in institutions, and tolerance for waiting, facilitating identification of intertemporal preferences that are otherwise difficult to observe. While absolute valuations of delay may vary across contexts, the underlying mechanisms identified here—risk-weighted time preferences, present-oriented valuation of protection, and heterogeneity by biological and social vulnerability—reflect general features of human health behavior rather than idiosyncratic local conditions.

This study makes three contributions. First, it provides a DCE-based quantification of intertemporal preferences for vaccination, recovering pronounced short-run impatience toward delayed protection, consistent with present-biased discounting in health investment decisions. Second, it demonstrates that sensitivity to delay is systematically patterned by biological and behavioral characteristics, including chronic medical conditions, preventive-health routines, and institutional trust, indicating that time preferences are shaped by perceived vulnerability and uncertainty rather than being purely individual traits. Third, by translating delay sensitivity into marginal willingness-to-accept measures, the analysis reveals that identical waiting periods impose unequal experiential burdens across the population, contribut-

ing to inequalities in the timing of health protection. Together, these findings position vaccination delay as a biologically consequential dimension of preventive behavior and underscore the importance of accounting for intertemporal preferences when studying health-related decision-making.

2. Theoretical Framework

Vaccination timing can be conceptualized as an investment in health capital, in which individuals weigh the immediate utility costs of uptake—such as effort, inconvenience, or anxiety—against the discounted preservation of future health stocks [9]. From this perspective, vaccination decisions are inherently intertemporal: postponing protection extends the period during which individuals remain biologically exposed to infectious risk. The discount parameters κ and δ therefore reflect not merely abstract time preferences, but valuations shaped by individuals' biological vulnerability and institutional environment. When future health returns are heavily discounted, even short delays impose substantial behavioural disutility, leading to underinvestment in timely preventive health.

Discrete choice experiments (DCEs) provide a structured approach to quantifying these intertemporal valuations by embedding vaccination delay directly into the latent utility associated with each alternative. Under an exponential specification, the utility of delayed protection declines at a constant rate δ, consistent with time-consistent valuation. In contrast, a quasi-hyperbolic specification allows discounting to be steeper over short horizons, capturing present-oriented preferences through the parameter κ. Rather than serving as purely technical objects, these parameters summarize how individuals trade off immediate burdens against delayed biological protection when exposure risk persists during waiting.

To capture how individuals *experience* waiting time rather than simply its objective duration, we derive a measure of subjective delay that links formal discounting to perceived temporal burden. This measure reflects the extent to which waiting for vaccination is psychologically inflated relative to calendar time, representing a behavioural "time tax" associated with remaining unprotected. Within this framework, the delay coefficient recovered from the DCE captures structural sensitivity to ongoing exposure rather than a purely logistical inconvenience. Variation in this sensitivity is expected to arise systematically from biological and health-related characteristics—such as age and chronic medical conditions—as well as from institutional

trust, which stabilizes expectations about future protection and reduces uncertainty surrounding delayed health returns. For clarity, we refer to the ratio between perceived and objective waiting time as the *Behavioral Delay Multiplier (BDM)*.

3. Methods

Our methodological approach integrates discrete choice modelling with a behavioral-economic framework to quantify how individuals value timely vaccination. Rather than treating waiting time as a logistical inconvenience, we embed delay directly into vaccine attributes and recover time-discount parameters from respondents' revealed trade-offs. This approach yields two economically interpretable quantities: the exponential discount factor δ, capturing how the value of protection declines with each month of delay, and the quasi-hyperbolic parameter κ, capturing present bias and the disproportionate weight placed on immediacy.

These parameters provide a welfare-relevant measure of the behavioral cost of delay. By mapping the delay coefficient onto marginal willingness-to-accept (MWTA), we estimate the implicit compensation individuals require to tolerate additional waiting time. Subgroup-specific estimates allow us to examine how delay aversion varies across demographic, behavioral, and institutional characteristics, providing a basis for identifying which groups may benefit most from reduced waiting times or early-access incentives.

The main text focuses on the conceptual and policy relevance of these parameters. All formal derivations—including the mapping from choice-model coefficients to δ, κ, and MWTA—are provided in Appendix C. This separation ensures transparency while keeping the primary narrative centred on the economic interpretation of timeliness in vaccination.

3.1. Study Design

We conducted a discrete choice experiment (DCE) to examine behavioral preferences for timely vaccination against COVID-like diseases (CLD).[1]

[1]Respondents were asked to consider a future "COVID-like disease" (CLD) scenario, defined as a hypothetical respiratory infection with severity and transmissibility comparable to COVID-19. This neutral framing enabled preference elicitation without anchoring responses to specific waves, variants, or personal experiences.

The CLD framing serves an important methodological function. By presenting a hypothetical respiratory pathogen with COVID-like transmissibility and severity, the design avoids anchoring responses to particular epidemic waves, personal experiences, or time-specific emotions associated with the original pandemic. This reduces recall bias, emotional spillover, and context-specific heuristics that may distort valuation of delay during or immediately after an actual outbreak. The CLD scenario therefore enables recovery of structural time-preference parameters—such as δ, κ, and MWTA—that generalise beyond COVID-19 and apply to a broader class of high-transmission respiratory diseases. This framing strengthens external validity while maintaining sufficient realism for respondents to make meaningful intertemporal trade-offs.

DCEs enable respondents to evaluate structured trade-offs between vaccine attributes and are widely applied in health-preference research [22, 14]. Although stated preferences may not perfectly mirror revealed behaviour, DCEs are extensively validated in preventive-health contexts and reliably recover marginal valuations of delay, convenience, and risk [22, 14, 15]. The survey was administered online in early 2025, when vaccination services were broadly available and respondents could reflect on vaccination timing outside acute epidemic pressures.

3.2. Sampling and Participants

The survey targeted adults living in Wuhan, China, using sampling strata for age, gender, and district to approximate the demographic composition of the city's adult population. Wuhan provides a theoretically meaningful setting for studying socially patterned vaccination behavior: its early and intense pandemic experience, strong public-health infrastructure, and high institutional visibility create a context in which differences in trust, information, and preventive routines are particularly salient. Eligibility criteria required respondents to be aged 18 or older, reside in Wuhan, and complete all survey modules. Standard attention and data-quality checks were applied. The final analytic sample consisted of 1,027 respondents. A comparison with the 2020 Wuhan Census benchmarks is provided in Appendix B.

3.3. DCE Attributes, Choice Tasks, and Experimental Design

Vaccine profiles were defined by five attributes: vaccination delay (0–6 months), vaccine efficacy, expected side effects, vaccine origin, and cash incentives. Each respondent completed six choice tasks, with each task present-

ing two vaccine alternatives and an opt-out option. An efficient fractional-factorial design was employed to ensure attribute balance and identification of main effects.

Prior to the main survey, the instrument was validated through a pilot study ($n = 60$) to assess attribute clarity and cognitive burden. Pilot results informed the selection of priors for the efficient design algorithm and indicated a mean completion time of 6.1 minutes, suggesting that task complexity was appropriate for the target population. The full choice card, including attribute definitions and pilot-based validity diagnostics, is provided in Appendix A.

3.4. Statistical Analysis

We estimated mixed logit models to recover preference distributions and account for unobserved heterogeneity in vaccination choices. Attribute coefficients were then used to derive implied exponential (δ) and hyperbolic (κ) discount parameters, following established behavioral-economic formulations [25]. These parameters quantify the degree to which respondents devalue delayed protection. Subgroup analyses examined variation by demographics, health behaviors, chronic medical conditions, and institutional trust, illuminating the social patterning of delay aversion.

We also computed marginal willingness-to-accept (MWTA) for vaccination delay by taking the ratio of the delay coefficient to the incentive coefficient. MWTA provides an economically interpretable measure of the implicit compensation individuals require to tolerate additional waiting time. All analyses were conducted in R using the `mlogit` and `gmnl` packages. Full model specifications, estimation details, and robustness checks—including alternative model structures, centering approaches, and repeated-choice diagnostics—are presented in Appendix C.

4. Results

4.1. Main Model Estimates

Table 1 summarizes the estimates from the conditional, multinomial, and mixed logit models based on the discrete choice experiment. To ensure comparability, coefficients were standardized to represent the change in utility associated with a one–standard-deviation change in each attribute.

In all models, *vaccine delay* was negatively associated with the probability of vaccine uptake, confirming that a longer delay substantially reduces willingness to vaccinate. Respondents showed strong positive preferences for vaccine efficacy and cash incentives, whereas side effects had weaker and less consistent associations with uptake.

Comparing magnitudes illustrates behavioral trade-offs: a one–standard-deviation increase in cash incentive offset nearly the entire disutility of a one–standard-deviation increase in vaccine delay, indicating that monetary incentives can effectively compensate for delay costs. Improvements in vaccine efficacy yielded similar gains, suggesting that respondents balance time, money, and protection when deciding whether to vaccinate.

The mixed logit model provided the best overall fit based on the log-likelihood and Akaike Information Criterion (AIC). Its random-parameter specification captures intra-individual preference correlation, providing a more flexible representation of heterogeneity. The significant standard deviation of the *multiple-delays* parameter in the mixed logit model indicates substantial variation in time sensitivity across respondents. Accordingly, the standardized coefficient for vaccine delays (-0.353) from the mixed logit model was used to estimate the hyperbolic and exponential discount parameters reported in the following tables.

Table 1 shows the comparison of logit models.

Table 1: Comparison of logit models (dependent variable: choice)

	Conditional logit	MNL (ASCs)	Mixed logit
Vaccine delays (std)	-0.131^{***} (0.019)	-0.125^{***} (0.020)	-0.353^{***} (0.027)
Vaccine efficacy (std)	0.153^{***} (0.036)	0.163^{***} (0.037)	0.218^{***} (0.041)
Side effects (std)	-0.042 (0.027)	-0.082^{***} (0.030)	0.008 (0.031)
Cash incentives (std)	0.327^{***} (0.018)	0.313^{***} (0.019)	0.431^{***} (0.025)
Vaccine origin (imported)	0.244^{***} (0.038)	0.239^{***} (0.038)	0.093^{**} (0.047)
Opt-out ASC		-0.214^{**} (0.093)	-0.287^{**} (0.118)
ASC: B		-0.108^{***} (0.033)	
ASC: C		-0.326^{***} (0.100)	
SD vaccine delays (std)			1.303^{***} (0.073)
Num. obs.	6162	6162	6162
Log likelihood	-6101.771	-6096.612	-5615.522
AIC	12215.543	12207.225	11245.044

Note: Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.2. Discount-Rate Estimation

From a biological perspective, steeper short-run discounting implies a higher perceived cost of remaining unprotected during ongoing exposure. Figure 1 presents the estimated discounting profiles from the exponential and hyperbolic models, fitted to the observed valuation points using a sum-of-squared-errors procedure. The x-axis shows the delay from 0 to 6 months, and the y-axis shows the corresponding discount factor. As expected, both curves begin at full value at zero delay and decline monotonically with increasing waiting time. The exponential model yields an estimated discount factor of $\delta = 0.160$, while the hyperbolic model yields $\kappa = 0.225$. The hyperbolic curve exhibits a sharp initial decline, particularly within the first three months, indicating pronounced present-oriented preferences and a strong valuation of immediacy in health protection. Appendix D reports subgroup-specific exponential and hyperbolic fits.

Beyond their behavioural interpretation, these discount parameters have well-defined economic meaning. In standard intertemporal choice and health-investment models, discount factors represent the rate at which individuals trade off present versus future health returns. Accordingly, δ and κ capture not only impatience but also the degree of intertemporal consistency and investment orientation in vaccination decisions, linking our estimates to foundational health-capital models and preventive behaviour theory. From a human-biology perspective, steeper short-run discounting implies a higher marginal biological cost of remaining unprotected, consistent with elevated perceived susceptibility to infection among medically vulnerable respondents. To link estimated discounting to experiential welfare, we also derive a Behavioral Delay Multiplier (BDM) that captures the inflation of subjective waiting time.

External Benchmarking of Discount Parameters. To assess external validity, we benchmarked our estimates against international evidence. Early DCE-based studies in the United Kingdom reported implied discount rates of 0.055–0.091 for one's own health and 0.078–0.147 for others' health [25]. Our estimates ($\delta = 0.160$, $\kappa = 0.225$) indicate steeper short-run impatience but remain within the broader empirical range of health-related discounting. Recent work documents similar patterns: Guillon, Béraud, and Vallée [12] identify impatience as a principal driver of COVID-19 vaccination; Attema, Brouwer, and Claxton [2] and Halilova et al. [13] demonstrate that present bias and higher discount rates reduce initiation and booster uptake;

and Soofi, Rashidi, and Tavakoli [29] estimate comparable β–δ parameters for preventive behaviours in Iran. Taken together, this evidence suggests that the impatience observed in Wuhan reflects a systematic behavioural regularity rather than a context-specific anomaly.

Contextual Salience of the Wuhan Setting. The magnitude of short-run impatience may partly reflect the heightened salience of vaccination during Wuhan's early-pandemic experience as the initial global epicentre of COVID-19, characterised by elevated risk awareness and institutional visibility. However, the underlying mechanisms—present bias, trust-conditioned valuation, and sensitivity to delay—are consistent with patterns documented across diverse international settings, suggesting that the behavioural processes identified here are generalisable even if the Wuhan context accentuates their magnitude.

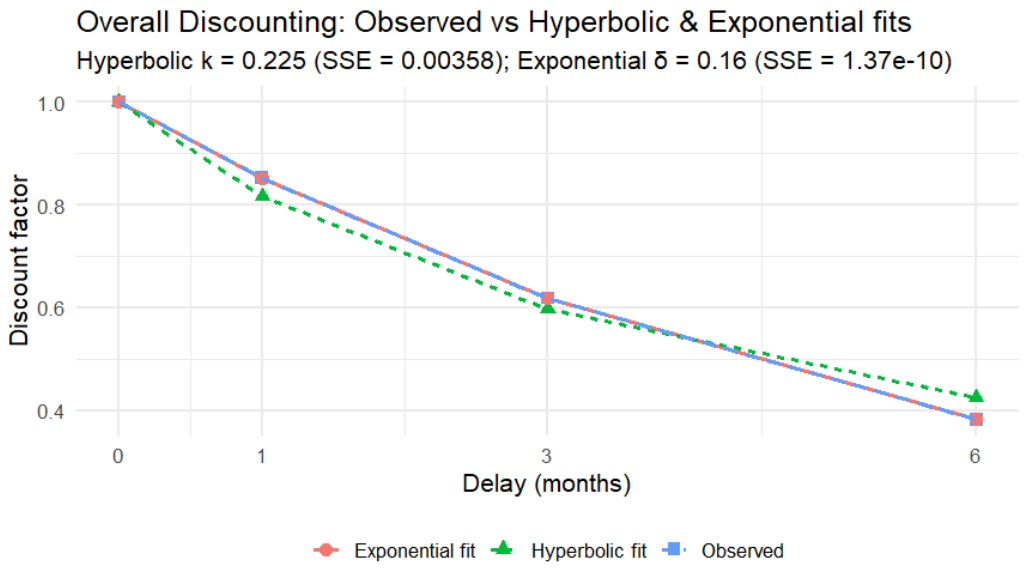

Figure 1: Comparison of observed discounting with hyperbolic and exponential fits.
Alt text: A line chart comparing observed discounting behaviour with fitted hyperbolic and exponential curves, showing close alignment in early months and divergence over longer delays.

4.3. Subgroup Heterogeneity

Table 2 summarizes the estimated hyperbolic and exponential discount rates across demographic, health–behavioral, prior vaccine reaction, and institutional-trust subgroups. For each subgroup, $\beta_{\text{delay}}^{(\text{std})}$ represents the standardized delay coefficient, while $\beta_{\text{delay}}^{(\text{month})}$ denotes the unstandardized marginal utility loss per month of vaccination delay. The transformation from waiting-time coefficients to the exponential and hyperbolic discount parameters (δ, κ) follows the derivation provided in Appendix C.6. Together, these indicators reveal how different population groups value the immediacy of protection.

Demographic heterogeneity. Clear demographic gradients emerged under both discounting models. Women exhibited slightly higher discount parameters than men, indicating greater impatience toward delayed vaccination and a stronger preference for prompt protection. Rural respondents, however, demonstrated lower discount rates relative to urban residents, suggesting stronger willingness to wait when faced with delays in vaccine availability. Age-related differences followed a nonlinear pattern: middle-aged adults (45–65 years) were the most patient, whereas younger (< 35 years) and older (≥ 65 years) adults displayed steeper discounting, consistent with previous evidence that these groups place greater weight on short-term benefits in health decisions. Educational differences were similarly nonmonotonic. Individuals with moderate education levels showed the highest patience, whereas those with very low or very high educational attainment exhibited stronger present bias. Both hyperbolic (κ) and exponential (δ) estimates produced low standard errors across subgroups, supporting the stability and internal consistency of the demographic patterns.

Health–behavioral heterogeneity. Time preferences also varied meaningfully across health behaviors and lifestyle factors. Smoking status and physical activity were examined to capture how routine health behaviors shape intertemporal vaccine decisions. Respondents who reported frequent smoking (*often*) and those engaging in moderate physical activity (*sometimes*) exhibited the lowest discount rates within their respective categories, indicating greater willingness to tolerate delayed vaccination. One interpretation is that individuals with more stable, habitual health routines may adopt a more flexible temporal orientation toward preventive interventions. By contrast, respondents with less regular health behaviors displayed steeper short-run discounting, consistent with behavioral-economic evidence linking irregular routines to stronger present bias.

Respondents reporting chronic medical conditions exhibited steeper discounting than those without such conditions. Consistent with a biological-risk interpretation, respondents reporting chronic medical conditions exhibited steeper discounting, implying that remaining unprotected carries a higher expected biological cost for individuals with elevated susceptibility to severe infection. Access to healthcare facilities contributed more modestly to delay sensitivity: respondents unable to reach a facility within 30 minutes showed slightly higher discount rates, indicating greater impatience. Prior adverse reactions to vaccines produced minimal differences, suggesting that past side-effect experiences did not substantially alter delay valuations in the context of COVID-like disease vaccination.

Table 2: Hyperbolic (κ) vs. Exponential (δ) parameters across demographic, behavioral, and institutional-trust subgroups

Group	n	$\beta_{\textbf{delay}}$ **(std)**	$\beta_{\textbf{delay}}$ **(per mo)**	κ / δ
Overall	1,027	-0.353^{***} (0.027)	-0.160^{***} (0.012)	0.225 / 0.160
Gender				
Female	545	-0.359^{***} (0.034)	-0.163^{***} (0.015)	0.230 / 0.163
Male	482	-0.346^{***} (0.036)	-0.157^{***} (0.016)	0.219 / 0.157
Residence				
Rural	555	-0.287^{***} (0.033)	-0.130^{***} (0.015)	0.174 / 0.130
Urban	472	-0.433^{***} (0.038)	-0.196^{***} (0.017)	0.290 / 0.196
Age group				
18–34	217	-0.327^{***} (0.054)	-0.148^{***} (0.024)	0.204 / 0.148
35–44	320	-0.420^{***} (0.042)	-0.190^{***} (0.019)	0.279 / 0.190
45–54	231	-0.292^{***} (0.051)	-0.132^{***} (0.023)	0.177 / 0.132
55–65	136	-0.237^{***} (0.059)	-0.107^{***} (0.027)	0.137 / 0.107
65+	123	-0.477^{***} (0.070)	-0.216^{***} (0.032)	0.327 / 0.216
Education				
No formal education	65	-0.442^{***} (0.093)	-0.201^{***} (0.042)	0.298 / 0.201
Primary school	226	-0.500^{***} (0.053)	-0.227^{***} (0.024)	0.348 / 0.227
Middle school	264	-0.265^{***} (0.049)	-0.120^{***} (0.022)	0.158 / 0.120
High school	210	-0.277^{***} (0.052)	-0.125^{***} (0.024)	0.166 / 0.125
College/University	160	-0.282^{***} (0.058)	-0.128^{***} (0.026)	0.170 / 0.128
Graduate	102	-0.458^{***} (0.063)	-0.208^{***} (0.029)	0.311 / 0.208
Smoking status				
Never	311	-0.367^{***} (0.043)	-0.167^{***} (0.020)	0.236 / 0.167
Sometimes	402	-0.392^{***} (0.039)	-0.178^{***} (0.018)	0.256 / 0.178
Often	314	-0.290^{***} (0.044)	-0.131^{***} (0.020)	0.176 / 0.131
Physical activity				
Rare	297	-0.455^{***} (0.046)	-0.206^{***} (0.021)	0.308 / 0.206
Sometimes	439	-0.304^{***} (0.037)	-0.138^{***} (0.017)	0.186 / 0.138
Quite often	291	-0.325^{***} (0.043)	-0.147^{***} (0.020)	0.202 / 0.147
Medical condition				
No	781	-0.300^{***} (0.029)	-0.136^{***} (0.013)	0.183 / 0.136

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Table 2 (continued)

Group	n	$\beta_{\textbf{delay}}$ **(std)**	$\beta_{\textbf{delay}}$ **(per mo)**	κ / δ
Yes	119	-0.355^{***} (0.070)	-0.161^{**} (0.032)	0.227 / 0.161
Healthcare access				
No access	460	-0.335^{***} (0.037)	-0.152^{***} (0.017)	0.211 / 0.152
Access	567	-0.368^{***} (0.034)	-0.167^{***} (0.015)	0.237 / 0.167
Prior vaccine reaction				
No	950	-0.352^{***} (0.027)	-0.159^{***} (0.012)	0.224 / 0.159
Yes	77	-0.372^{***} (0.092)	-0.168^{**} (0.042)	0.240 / 0.168
Institutional trust				
Strongly distrust	93	-0.327^{***} (0.072)	-0.148^{***} (0.033)	0.204 / 0.148
Somewhat distrust	133	-0.317^{***} (0.072)	-0.144^{***} (0.032)	0.196 / 0.144
Neutral	261	-0.510^{***} (0.052)	-0.231^{***} (0.023)	0.356 / 0.231
Somewhat trust	267	-0.278^{***} (0.045)	-0.126^{***} (0.020)	0.167 / 0.126
Strongly trust	179	-0.268^{***} (0.054)	-0.122^{***} (0.025)	0.160 / 0.122

Notes: Standard errors in parentheses. n indicates the number of respondents per subgroup. p-values adjusted via Benjamini–Hochberg false-discovery rate ($q = 0.10$); Holm–Bonferroni corrections yield similar results. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

To synthesize the subgroup patterns, Figure 2 visualizes the estimated hyperbolic discount parameters (κ) across demographic, behavioral, health-status, and institutional-trust groups. The figure highlights the broad dispersion in delay sensitivity, with certain groups exhibiting markedly steeper present-oriented preferences than others. Higher values of κ cluster among subgroups characterised by greater uncertainty or social vulnerability, whereas lower values appear among groups with stronger health engagement or stability in preventive behaviours. The visualization makes clear that time preferences for vaccination are heterogeneous rather than uniform, reinforcing the need for tailored strategies that account for these uneven behavioral costs of waiting.

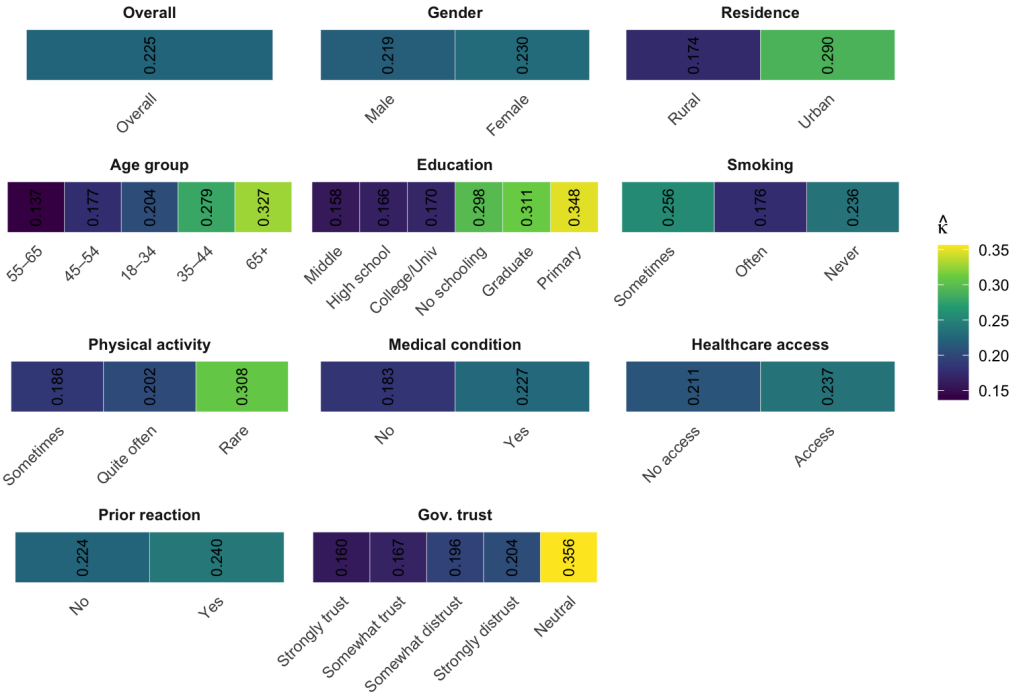

Figure 2: Subgroup variation in hyperbolic discount parameters (κ). Higher values indicate stronger present-oriented preferences (greater impatience toward vaccination delay). Clear social and behavioral gradients appear across education, age, physical activity, medical vulnerability, and trust in government.

4.4. Marginal Willingness-to-Accept (MWTA)

Table 3 reports the implied marginal willingness-to-accept (MWTA) for one month of delay. Across the full sample, respondents required approximately 45–56 RMB in compensation per month of waiting, reflecting substantial short-run impatience. These MWTA estimates align closely with the subgroup differences observed in the discount parameters: individuals with lower institutional trust, lower education, or irregular preventive-health routines consistently demanded higher compensation for delay.

Economic Interpretation of MWTA and Heterogeneous Delay Sensitivity.. MWTA provides a monetary expression of the behavioural cost of waiting and translates the estimated delay coefficients into an economically interpretable metric. Subgroup comparisons reveal pronounced heterogeneity. Respondents with low trust, lower education, chronic conditions, or irregular preventive routines exhibit substantially higher MWTA values, indicating that these groups perceive delay as more costly and place greater value on immediacy. These patterns align with their steeper short-run discounting and elevated κ estimates.

This heterogeneity has direct implications for the cost–benefit evaluation of vaccination strategies. Groups with high MWTA values stand to gain disproportionately from even modest reductions in waiting time, suggesting that interventions such as queue-shortening, priority scheduling, or rapid-access appointments generate especially large behavioural returns in these populations. Conversely, broad, non-targeted convenience improvements may deliver smaller marginal benefits among low-MWTA groups who are more tolerant of delay.

Subgroup-specific MWTA estimates also inform the efficient targeting of financial or quasi-financial incentives. Because high-MWTA groups respond more strongly to reductions in delay—or to modest, immediate rewards—allocating a greater share of incentives or operational resources toward these populations may maximise uptake per yuan spent. Taken together, this framework provides an economically grounded rationale for identifying where behavioural interventions, convenience enhancements, or early-rollout policies can generate the highest return on public-health investment.

MWTA offers a practical lens for policy design. Because reducing waiting time is often far cheaper and operationally easier than providing financial incentives, MWTA helps identify when logistical improvements may deliver greater uptake per yuan spent. For the average respondent, a one-month

Table 3: Marginal willingness-to-accept (MWTA) for one month of delay

Group	MWTA	SE	Sig.
Overall sample	52.1	7.4	***
Low institutional trust	81.3	10.9	***
High institutional trust	34.2	6.8	***
Irregular physical activity	68.9	9.5	***
Regular physical activity	31.4	5.7	***

Note: MWTA is expressed in RMB. SE denotes standard error.

reduction in delay generates the same behavioural gain as roughly 50 RMB in incentives, with even larger returns among high-delay-aversion groups. This makes queue-shortening, extended clinic hours, or streamlined scheduling potentially more cost-effective tools than additional cash rewards.

To aid interpretation, Figure 3 visualizes a "Policy Trade-Off Menu" that translates these MWTA estimates into an intuitive comparison between time and money. Panel A standardizes the utility gain from reducing waiting time by one month, and Panel B shows the cash incentive required to offset that same delay for each subgroup.

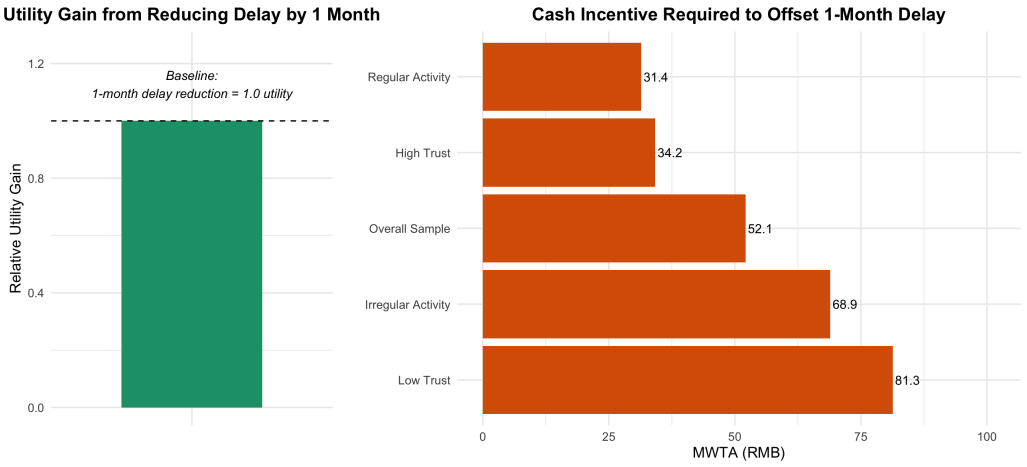

Figure 3: Policy trade-off menu: monetary equivalents of reducing vaccination delay by one month. Panel A standardizes the utility gain from reducing waiting time by one month at 1.0 (dashed reference line). Panel B shows the cash incentive required to offset the same delay across subgroups (e.g., about 81 RMB for low-trust respondents versus about 31 RMB for respondents with regular preventive routines).

5. Discussion

This study examined how individuals value timely vaccination for COVID-like diseases (CLD) using a discrete choice experiment embedded within a behavioural-economic framework. Three central insights emerge. First, respondents exhibited short-run impatience, discounting delayed protection and requiring compensation for even modest waiting times. Second, these patterns align with established theories of present bias and quasi-hyperbolic discounting, indicating that vaccine delay reflects systematic intertemporal preferences rather than solely access constraints. Third, pronounced demographic, behavioural, and institutional gradients show that delay aversion is socially patterned and linked to broader determinants of preventive behaviour. While these absolute valuations may be upward-biased due to hypothetical decision-making, the underlying behavioural patterns remain stable across subgroups and align with international evidence. *Although stated preferences may not perfectly match real incentive-consistent behaviour, extensive evidence shows that DCE-derived valuations of delay and convenience reliably predict uptake patterns in preventive-health contexts* [15, 14, 16].

5.1. Behavioural Mechanisms Underlying Vaccine Delay

The pattern of discounting observed here is consistent with evidence that vaccination decisions place substantial weight on short-term frictions relative to delayed health benefits [25, 2, 3], indicating particularly strong preferences for immediacy in vaccination decisions. Respondents placed disproportionate weight on short-term inconveniences and side-effect concerns relative to delayed and uncertain health benefits. The steep early decline in the hyperbolic curve likely captures the cumulative psychological burden of logistical frictions, which multi-country evidence identifies as key bottlenecks in pandemic vaccination [16]. These tendencies intensify under uncertainty and perceived risk ambiguity [6]. The pattern is consistent with experimental evidence on near-term impatience [19, 24] and helps explain the "strategic delay" behaviour documented in prior campaigns [21, 31].

Subjective Waiting Time and the Behavioral Delay Multiplier (BDM).. To connect discounting behaviour to experiential perceptions of delay, we compute the *Behavioral Delay Multiplier* (BDM). As derived in Appendix C9, the BDM is defined as the ratio between the perceived and objective duration of waiting, providing a behavioural measure of *subjective waiting time*.

While the average BDM is 1.29, this inflation is even more pronounced among vulnerable subgroups: low-trust respondents and individuals with chronic conditions exhibit BDM values approaching 1.5, meaning that a 30-day delay is experienced as the equivalent of 45 days. We interpret this divergence between objective and subjective time as a *psychological time tax* disproportionately borne by socially and medically vulnerable populations. Incorporating subjective waiting time into policy design clarifies why some groups respond strongly to even modest changes in waiting time and supports prioritising delay-reducing interventions for these populations.

5.2. Biological Vulnerability and Intertemporal Health Investment

Intertemporal preferences for vaccination timing are best understood not as abstract measures of impatience, but as responses shaped by biological vulnerability and exposure risk. When individuals face elevated baseline health risks, each day of delayed protection carries a greater expected biological cost. Steeper short-run discounting, in this light, reflects an adaptive valuation of immediacy under uncertainty—a rational response to risk rather than a departure from optimal health investment [11, 3].

This interpretation finds support in the elevated delay sensitivity observed among respondents with chronic medical conditions. Chronic illness—whether cardiovascular, metabolic, or respiratory—compromises immune function, diminishes physiological reserves, and heightens susceptibility to severe infection outcomes. For these individuals, remaining unprotected is not merely inconvenient; it represents a period of amplified biological exposure. From a health-capital perspective, poorer baseline health steepens the risk gradient over time, making delayed vaccination disproportionately costly. The stronger preference for immediacy in this group thus reflects risk-weighted decision-making rather than generalized behavioural bias [5, 6].

Age-related patterns reinforce this logic. Both younger and older adults exhibit steeper discounting than middle-aged respondents, but for distinct biological and behavioural reasons. Among older adults, immunosenescence—the progressive decline in immune competence with age—elevates both infection risk and disease severity, providing a clear physiological basis for urgency. For younger adults, steeper discounting may instead reflect greater uncertainty about future behavioural follow-through or competing life demands. In both cases, time preferences track perceived vulnerability across the life course rather than reflecting uniform impatience [20, 32].

Institutional trust introduces a further layer of complexity. Lower trust heightens uncertainty about whether delayed vaccination will ultimately deliver its promised benefits—whether due to concerns about vaccine availability, quality, or institutional follow-through. Under such uncertainty, discounting future protection more steeply becomes a coherent response: if the probability of receiving effective protection diminishes, the rational weight placed on that future benefit declines accordingly. Trust, in this framework, functions as intertemporal capital—stabilising expectations about future health returns and thereby attenuating present bias [6, 4].

Taken together, these findings suggest that heterogeneity in vaccination timing preferences reflects adaptive responses to biological and institutional risk rather than idiosyncratic variation in patience. Viewing delay aversion through this lens clarifies why identical waiting periods impose unequal burdens across populations: for the chronically ill, the elderly, and those lacking institutional trust, each day of delay carries greater weight. This perspective underscores the importance of integrating biological vulnerability into analyses of intertemporal health behaviour and challenges interpretations that treat time preferences as stable, context-independent traits.

5.3. The Unequal Burden of Delay: Quantifying the Regressive "Time Tax"

Waiting for vaccination is not costless. Our MWTA estimates quantify this burden: respondents required approximately 52 RMB per month to tolerate delay, a valuation comparable to modest cash incentives offered during actual vaccine campaigns. This figure captures something beyond monetary trade-offs—it reflects how individuals experience waiting as a salient friction, even when vaccines are nominally free.

Real-world benchmarks contextualise this magnitude. During the COVID-19 rollout, local governments in China and the United States deployed cash transfers of 200–300 RMB (USD 30–45) to encourage uptake [23, 30]. That our MWTA estimates fall below these thresholds suggests stated preferences may conservatively estimate the true experiential cost of delay, particularly in high-uncertainty environments. Even so, the results demonstrate that modest reductions in waiting time can meaningfully shift the perceived attractiveness of vaccination.

The aggregate, however, conceals pronounced inequality. As Figure 3 illustrates, the value placed on immediacy is socially patterned. High-trust individuals value a one-month reduction in delay at approximately 34.2 RMB;

low-trust individuals value the same reduction at 81.3 RMB—a 2.4-fold difference. Waiting, in effect, functions as a regressive "Time Tax," extracting greater psychological cost from those who already face heightened uncertainty about future protection [4].

We use "Time Tax" metaphorically rather than literally: the burden is experiential, not financial. Yet the implication is concrete. Identical delays generate vastly different consequences across groups—what constitutes a minor inconvenience for the trusting becomes a substantial barrier for the sceptical.

These patterns carry a clear message: delays in vaccination access are not neutral administrative features. They are uneven temporal burdens, shaped by vulnerability and institutional trust. Uniform rollout schedules that ignore this heterogeneity risk concentrating the costs of waiting precisely where they are hardest to bear—among populations already navigating greater uncertainty and fewer resources for timely protection.

Policy Actions. These findings indicate that uniform vaccination rollout strategies are experienced very differently across populations when supply or delivery capacity is constrained. Groups characterized by high delay aversion—such as individuals with lower institutional trust or lower educational attainment—exhibit particularly strong behavioral responses to reductions in waiting time. For these populations, prolonged delays translate into disproportionately large experiential and behavioral barriers to uptake. Institutional features that shorten waiting times, including fast-tracking mechanisms, priority appointment slots, or mobile vaccination units, may therefore substantially reduce barriers to timely protection among delay-sensitive groups.

By contrast, individuals with lower sensitivity to delay—such as those with higher institutional trust or more regular preventive health routines—appear more tolerant of moderate waiting periods. For these groups, maintaining transparent, predictable, and reliable scheduling may be sufficient to sustain vaccination uptake, even in the presence of limited capacity. Recognizing this heterogeneity highlights how uniform delivery schedules can concentrate the burdens of delay among populations already facing greater uncertainty or vulnerability. Accounting for group-specific sensitivity to waiting time clarifies how vaccination delivery arrangements shape unequal experiences of access and timeliness across the population.

5.4. Limitations

Several limitations should be noted. First, as with all stated-preference studies, hypothetical bias may inflate absolute MWTA and discounting magnitudes. However, the survey design incorporated multiple features intended to approximate real-world vaccination decisions, including realistic attribute ranges informed by pilot testing, repeated choice scenarios, dominance checks, and an opt-out option. The very low rate of dominance violations and the consistency of subgroup gradients suggest that the behavioural patterns identified are robust, even if absolute valuations are upward-biased [22, 15].

Second, the sample comprises adults in Wuhan, a high-salience pandemic context, and the DCE captures static, one-shot trade-offs rather than dynamic influences such as evolving risk perceptions or social learning [21, 31]. While absolute effect sizes may vary in lower-salience settings, the structural relationships between delay aversion, institutional trust, and preventive behaviour are theoretically portable and empirically observable across populations. Future work should examine how intertemporal preferences evolve across outbreak phases.

Third, the study relies on self-reported chronic disease status rather than verified medical records or biomarkers. Future research could strengthen the biological interpretation by incorporating objective health measures—such as HbA1c for diabetes management or inflammatory markers—to validate the link between physiological vulnerability and delay aversion.

6. Conclusion

This study shows that behavioral impatience is not merely an individual preference parameter but a systematic feature of how individuals experience the timing of vaccination under risk. By quantifying the value placed on immediacy, we demonstrate that steep short-run discounting renders waiting time a salient friction even when vaccines are nominally free, and that this friction varies substantially across populations. Delays in access therefore translate into unequal periods of biological exposure rather than uniform administrative inconvenience.

Approaches that focus solely on compensating individuals for delay, such as financial incentives, address the consequences of delayed uptake without altering the underlying temporal frictions shaping vaccination decisions. More generally, heterogeneity in delay aversion implies that identical rollout schedules are experienced very differently across groups, generating unequal

behavioral and health-relevant burdens. Interpreting institutional trust as a form of intertemporal capital helps explain why the same delivery timelines produce divergent responses, as confidence in future protection stabilizes expectations and reduces the perceived cost of waiting.

Recognizing behavioral time costs as a dimension of preventive health behavior highlights the importance of institutional features that shape when protection is received, not only whether it is available. Accounting for intertemporal frictions clarifies how seemingly neutral waiting periods can amplify disparities in the timing of health protection, especially among populations facing greater biological vulnerability or uncertainty. These findings underscore the need to consider how vaccination delivery schedules interact with intertemporal preferences when evaluating the population-level experience of preventive interventions.

Declaration of Generative AI Use

Generative artificial intelligence tools (including ChatGPT) were used to assist with language editing, formatting, and clarification of exposition during manuscript preparation. These tools were not used to generate data, conduct analyses, interpret results, or draw scientific conclusions. All analyses and interpretations were performed by the authors, who take full responsibility for the content of the manuscript.

Ethics approval and informed consent

The study involved anonymous, minimal-risk survey research conducted in China. All study procedures complied with relevant national regulations and institutional guidelines. The study protocol was reviewed by an appropriate institutional ethics committee and determined to require no formal ethics approval. All participants provided informed consent prior to participation.

Data Availability Statement

The data that support the findings of this study are not publicly available due to ethical and privacy considerations related to human-subject survey data. De-identified data may be made available from the corresponding author upon reasonable request, subject to approval by the relevant ethics committee.

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Appendix A. DCE Instrument, Choice Tasks, and Validity Diagnostics

This appendix presents the diagnostic checks used to assess internal validity in the discrete choice experiment (DCE), including (i) dominance behaviour, (ii) attribute non-attendance (ANA), (iii) transitivity and consistency, (iv) intra-individual variable correlations, and (v) pilot-study procedures. Collectively, these checks support the internal reliability and behavioural coherence of the responses.

A.1 Dominance Behaviour

Dominance tests evaluate whether respondents ever selected an alternative that was strictly dominated across all attributes. As shown in Table A1, only 1.8% of respondents violated dominance at least once—well within the $\leq 5\%$ threshold commonly considered acceptable in DCE research [22, 15]. This low rate suggests that respondents understood the choice tasks and engaged in meaningful trade-offs.

A.2 Attribute Non-Attendance (ANA)

ANA analyses assess whether respondents systematically ignored particular attributes during choice tasks. Table A1 indicates that ANA was 0% for vaccine delay, efficacy, side-effects, and cash incentives, reflecting strong salience of the primary decision attributes. A small minority (5.4%) showed insensitivity to vaccine origin, suggesting minor simplification but no evidence of widespread attribute non-attendance. Overall, ANA diagnostics demonstrate robust engagement with the full attribute structure.

Table .4: Dominance behaviour and attribute non-attendance (ANA)

Check	**Definition**	**Result (%)**
Dominance rate	Share selecting a dominated alternative	1.8
ANA: Vaccine delays	Choices invariant to delay levels	0.0
ANA: Vaccine efficacy	Choices invariant to efficacy levels	0.0
ANA: Side effects	Choices invariant to side-effect levels	0.0
ANA: Cash incentives	Choices invariant to cash levels	0.0
ANA: Vaccine origin	Choices invariant to origin levels	5.4

Note. Dominance reflects selecting an option strictly inferior across all attributes. ANA indicates choices unaffected by variation in a given attribute across tasks.

A.3 Transitivity and Choice Consistency

Respondents' choices satisfied the transitivity assumptions of random utility theory. No systematic violations or preference reversals were detected, and repeated patterns across the six tasks reflected stable and ordered preferences. These findings support the internal consistency and construct validity of the DCE, reinforcing the reliability of the resulting preference and time-discount parameter estimates.

A.4 Correlation Matrix of Intra-Individual Variables

Figure A1 displays pairwise correlations across all individual-level covariates included in the mixed-logit and subgroup models. All coefficients were below 0.10, indicating minimal concerns regarding multicollinearity or redundancy.

Access to healthcare showed only weak associations with other variables. Government trust was slightly positively correlated with age and rural residence, while smoking exhibited a weak negative correlation with chronic medical conditions. Overall, these low correlations confirm sufficient distinctness across covariates for use in the multivariate analyses.

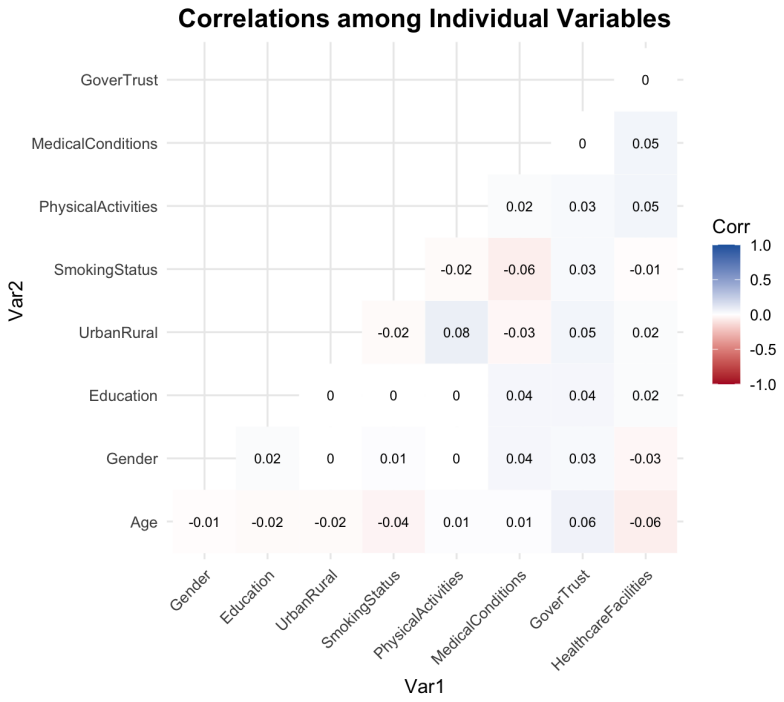


Figure .4: Correlation matrix of individual-level covariates. Darker colours indicate stronger correlations. All coefficients are below 0.10, confirming negligible multicollinearity.

A.5 Example Choice Task

Figure A2 provides an example of the choice task presented to respondents. Each task featured two hypothetical vaccine profiles varying across five attributes—delay to vaccination, origin, efficacy, side-effect severity (supported by illustrative icons), and cash incentives—and an opt-out alternative. Attribute descriptions appeared at the top of the screen. For example, efficacy was defined behaviourally as the percentage reduction in infection risk ("95% effectiveness means a 95% reduction in infection risk"), and side effects were described using both text and images to reduce cognitive burden.

The example shown contrasts two vaccines identical in origin and efficacy but differing in delay (0 vs. 1 month), side-effect severity (fatigue for one week vs. fever lasting two days), and incentives (800 CNY vs. 200 CNY).

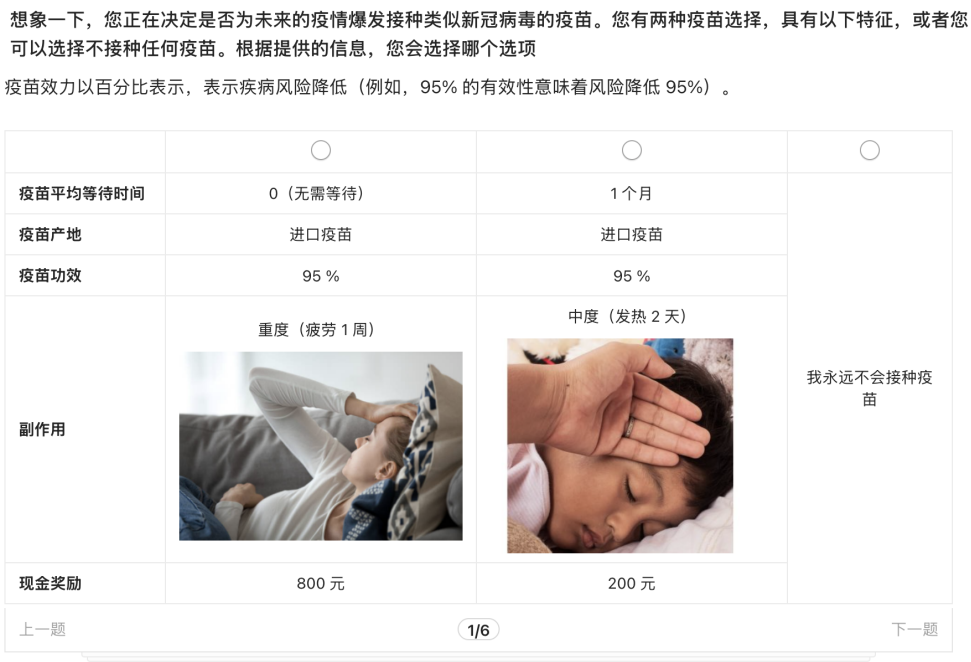


Figure .5: Example DCE choice task shown to respondents. Participants selected between two hypothetical vaccine profiles or an opt-out option.

A.6 Pilot Study Procedures

A pilot study was conducted with 60 adults from Wuhan to assess the clarity, feasibility, and cognitive burden of the DCE instrument. The pilot followed the same screening criteria as the main study and included the full sequence of choice tasks, sociodemographic questions, and a debriefing module.

The pilot served three purposes. First, it evaluated comprehension of attribute descriptions and level wording. Respondents demonstrated clear understanding of delay, efficacy, and side-effect attributes, while minor revisions were made to simplify phrasing for vaccine origin and severity icons.

Second, the pilot assessed task difficulty and respondent burden. Completion times ranged from 4.7 to 10.2 minutes (mean: 6.1) , indicating that the number of tasks and cognitive demands were appropriate. Dominance and ANA rates were consistent with those in the main sample, suggesting no evidence of satisficing or disengagement.

Third, the pilot refined the statistical efficiency of the experimental design. Preliminary parameter estimates informed updated priors in the efficient design algorithm, improving attribute balance and orthogonality in the final DCE.

Overall, pilot results confirmed that the survey instrument was clear, feasible, and capable of generating high-quality preference data.

Appendix B. Sample Representativeness and Census Benchmarking

This appendix evaluates the representativeness of the analytic sample ($N = 1{,}027$) by comparing key demographic characteristics with benchmarks from the 2020 Wuhan Census [33]. Sampling of the quotes ensured the alignment in gender, age, and district of residence. As shown in Table .5, the sample closely approximates the demographic profile of Wuhan's adult population. Minor differences—such as a slightly higher proportion of college-educated respondents—are typical of online survey panels and were further examined through robustness and weighting analyses.

Table .5: Comparison of Analytic Sample with 2020 Wuhan Census Benchmarks

Characteristic	**Sample (%)**	**Wuhan Census (%)**
Gender		
Female	53.0	51.1
Male	47.0	48.9
Age Distribution		
18–34	21.0	23.9
35–44	31.2	28.6
45–54	22.5	21.7
55–65	13.2	14.3
65+	12.0	11.5
Residence		
Urban	47.0	48.3
Rural	53.0	51.7
Education Level		
No formal schooling	4.0	5.6
Primary school	22.0	24.3
Middle school	25.7	27.1
High school	20.4	21.7
College/University	15.6	13.4
Graduate degree	11.0	7.9

Note. Census benchmarks are drawn from the Wuhan Bureau of Statistics[33]. Deviations follow typical patterns in online survey panels. Post-stratification weighting yielded mixed-logit and discount-rate estimates substantively identical to unweighted results (Appendix C).

Summary of Sample Representativeness

- Survey sampling produced close alignment with Wuhan's 2020 Census for gender, age, and urban–rural residence.
- Slight upward shift in college-educated respondents is consistent with online panel sampling.
- Pearson χ^2 tests indicate no statistically significant difference between sample and population distributions at the 5% level.
- Weighted and unweighted mixed-logit models produced nearly identical results, confirming robustness to demographic composition (see Appendix C).

To formally evaluate representativeness, Pearson χ^2 tests were conducted for gender, age group, and residence. All tests were statistically non-significant at the 5% level, indicating no systematic deviation from Wuhan's adult population. Weighted mixed-logit models yielded parameters nearly identical to those in the unweighted sample, reinforcing the robustness of the main findings.

Appendix C Model Estimation Details

This appendix provides additional detail on the estimation of the mixed logit models and the derivation of exponential and hyperbolic discount parameters used in the main analysis.

C1. Utility Specification

We adopt a random–utility framework in which individual i evaluates vaccine alternative j in choice task t according to:

$$U_{ijt} = \beta_0 + \beta_1 \,\text{VaccineDelay}_{\text{std},ijt} + \beta_2 \,\text{VaccineOrigin}_{\text{std},ijt} + \beta_3 \,\text{VaccineEfficacy}_{\text{std},ijt} + \beta_4 \,\text{SideEffects}_{\text{std},ijt} + \beta_5 \,\text{CashIncentives}_{\text{std},ijt} + \varepsilon_{ijt}, \tag{C1}$$

where ε_{ijt} follows an i.i.d. Type I extreme-value distribution. For comparison, both conditional logit (MNL) and mixed logit (MXL) models were estimated, but the MXL is the preferred specification because it allows random coefficients to capture unobserved preference heterogeneity.

In vector notation:

$$U_{ijt} = \beta_0 + \sum_{k=1}^{K} \beta_k X_{k,ijt} + \varepsilon_{ijt}, \tag{C2}$$

Standardization of the attribute coefficients facilitates comparison across attributes and inputs directly into the discount-rate estimation procedure described below.

C2. Discount Function Specification

Observed delay levels $t \in \{0, 1, 3, 6\}$ months are mapped to standard exponential and hyperbolic discounting frameworks:

$$D_{\text{Exp}}(t; \hat{\delta}) = e^{-\hat{\delta} t}, \qquad \hat{\delta} \geq 0, \tag{C3}$$

$$D_{\text{Hyper}}(t; \hat{\kappa}) = \frac{1}{1 + \hat{\kappa} t}, \qquad \hat{\kappa} \geq 0. \tag{C4}$$

These formulations correspond to time-consistent (exponential) and present-biased (hyperbolic) discounting, respectively.

C3. Constructing Observed Discount Points

Let $\beta_{\text{delay (per month)}}$ be the unstandardized coefficient from the secondary model in which delay is entered linearly. This coefficient represents the marginal utility loss associated with a one-month increase in delay. It is recovered from the standardized coefficient via:

$$\beta_{\text{delay (per month)}} = \frac{\beta_{\text{delay (std)}}}{\text{SD(MultipleDelays)}}. \tag{C5}$$

Following standard practice in preventive-health time-preference studies, we define the utility-consistent "observed" discount factor for each delay t as:

$$D_{\text{obs}}(t) = \exp\left(-\beta_{\text{delay (per month)}}\, t\right). \tag{C6}$$

These points serve as empirical inputs for fitting exponential and hyperbolic discount functions.

C4. Estimation of Discount Parameters

The exponential and hyperbolic discount parameters are obtained by minimizing the sum of squared errors (SSE) between the observed and theoretical discount functions.

Hyperbolic fit..

$$\text{SSE}_{\text{Hyper}}(\hat{\kappa}) = \sum_{i=1}^{n} \left[D_{\text{obs}}(t_i) - D_{\text{Hyper}}(t_i; \hat{\kappa})\right]^2. \tag{C7}$$

The first-order condition is:

$$\frac{\partial}{\partial \kappa}\text{SSE}_{\text{Hyper}}(\kappa) = 2\sum_{i=1}^{n}\left(D_{\text{obs}}(t_i) - \frac{1}{1+\kappa t_i}\right)\frac{t_i}{(1+\kappa t_i)^2} = 0, \qquad \text{evaluated at } \kappa = \hat{\kappa}. \tag{C8}$$

Exponential fit.

$$\text{SSE}_{\text{Exp}}(\hat{\delta}) = \sum_{i=1}^{n}\left[D_{\text{obs}}(t_i) - D_{\text{Exp}}(t_i; \hat{\delta})\right]^2. \tag{C9}$$

First-order condition:

$$\frac{\partial}{\partial \delta}\mathrm{SSE}_{\mathrm{Exp}}(\delta) = 2\sum_{i=1}^{n}\left(D_{\mathrm{obs}}(t_i) - e^{-\delta t_i}\right) t_i e^{-\delta t_i} = 0, \qquad \text{evaluated at } \delta = \hat{\delta}. \tag{C10}$$

Closed-form solutions do not exist; parameters were estimated via nonlinear least squares.

C5. Subgroup Estimation and Multiplicity

Subgroup-specific MXL models were estimated separately for demographic, behavioural, health-status, and institutional-trust categories. Because this involves multiple hypothesis tests, p-values for subgroup delay coefficients were adjusted using the Benjamini–Hochberg false-discovery rate (FDR) at $q = 0.10$. Robustness of subgroup differences was confirmed under Holm–Bonferroni corrections.

C.6 Recovering Discount Parameters from Waiting-Time Coefficients

To recover exponential discount parameters from the DCE model, we map the estimated waiting-time coefficient β_{delay} to the implied monthly discount factor δ. Under exponential discounting, utility declines with delay according to $U(t) = U_0\delta^t$. A first-order approximation yields a linear representation in which the marginal disutility of delay corresponds to the logarithm of the discount factor. Normalizing the baseline utility $U_0 = 1$ implies:

$$\hat{\delta} = \exp\left(\hat{\beta}_{\mathrm{delay}}\right).$$

Thus, more negative values of β_{delay} correspond to lower discount factors and stronger impatience toward delayed protection. This transformation is used to obtain the discount parameters reported in Table 2.

C.7 MWTA Derivation

The marginal willingness-to-accept (MWTA) for one month of delay is derived as the ratio of the delay coefficient to the cash-incentive coefficient:

$$\mathrm{MWTA} = -\frac{\beta_{\mathrm{delay}}}{\beta_{\mathrm{cash}}}.$$

This represents the monetary compensation required to offset the disutility of an additional month of waiting.

C8. Additional Diagnostics

We conducted additional diagnostic checks, including model comparison (AIC and log-likelihood), scale-heterogeneity assessment using a GMNL specification, and re-estimation excluding potential speeders. Across all alternative specifications, the sign, magnitude, and statistical significance of the delay coefficient remained highly stable, and the implied discount parameters were unchanged. These results confirm that the main findings are robust to functional-form assumptions and response-quality concerns. Full model outputs are available upon request.

C9. Behavioral Delay Multiplier (BDM)

To provide an intuitive interpretation of the hyperbolic discount parameter, we compute a Behavioral Delay Multiplier (BDM), defined as:

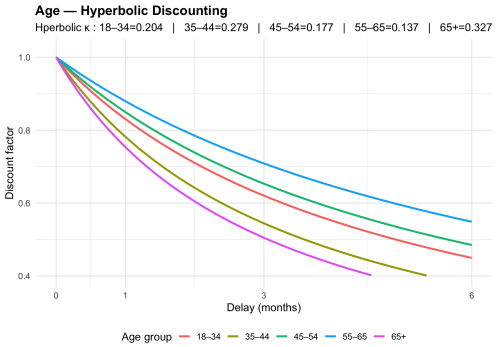
$$\text{BDM} = \frac{1}{1 - \hat{\kappa}}, \tag{C11}$$

which rescales the estimated hyperbolic parameter into a measure of the perceived cost of waiting. A value greater than 1 indicates that each month of objective delay is experienced as a longer *behavioural* delay. For example, the overall estimate $\hat{\kappa} = 0.225$ implies a BDM of 1.29, meaning that one month of waiting feels equivalent to approximately 1.29 months. Subgroups with larger $\hat{\kappa}$—such as older adults, respondents with primary education, or those reporting neutral trust in government—exhibit BDM values between 1.45 and 1.55, indicating substantially amplified perceived waiting costs. In contrast, groups with smaller $\hat{\kappa}$, including rural residents and individuals reporting regular physical activity, show BDM values near 1.15–1.20, reflecting weaker behavioural sensitivity to delay. This multiplier offers a transparent summary measure that complements the formal discount-rate estimates presented in Sections C2–C4.

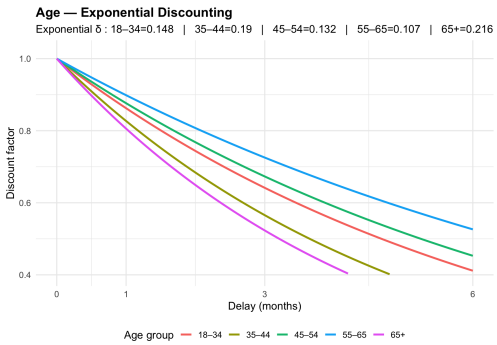
Table .6: Behavioral Delay Multiplier (BDM) for Selected Subgroups

Subgroup	$\hat{\kappa}$	**BDM**	**Interpretation**
Overall sample	0.225	1.29	1 month feels like 1.29 months
Urban residents	0.290	1.41	Higher perceived waiting cost
Rural residents	0.174	1.21	Lower perceived waiting cost
Primary education	0.348	1.53	Amplified behavioural delay
Adults aged 65+	0.327	1.49	Delay feels substantially longer
Neutral trust in gov.	0.356	1.55	Strongest impatience

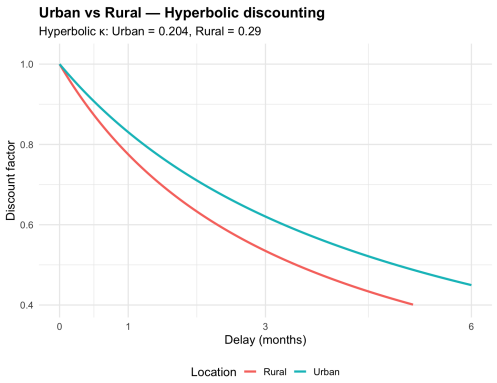
Appendix D. Subgroup-specific Discounting Plots



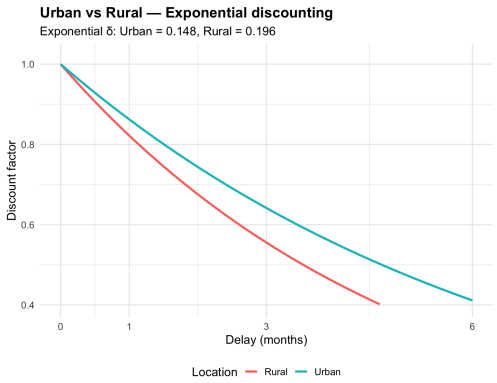
Panel A: Age-specific discounting. Five age groups (18–34, 35–44, 45–54, 55–65, 65+).



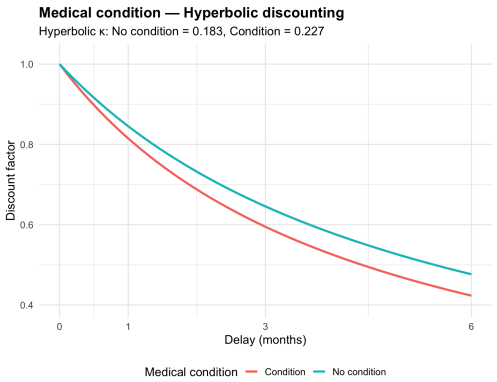
Five age groups (18–34, 35–44, 45–54, 55–65, 65+).



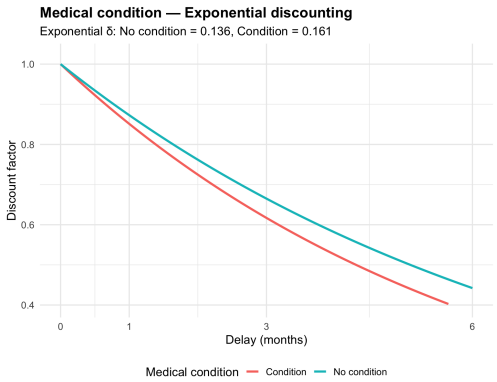
Panel B: Location-specific discounting



Urban vs rural respondents.

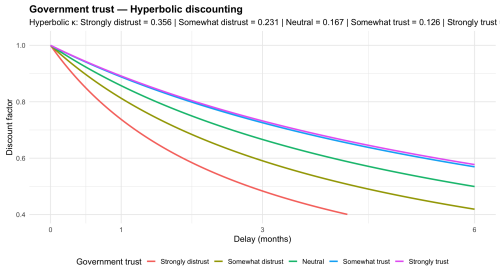


Panel C: Medical condition–specific discounting

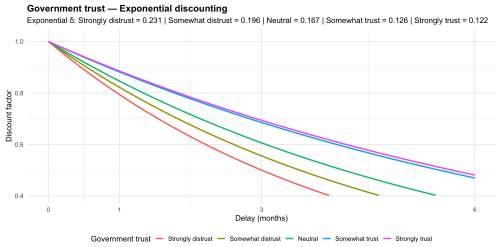


Individuals with vs without medical conditions.

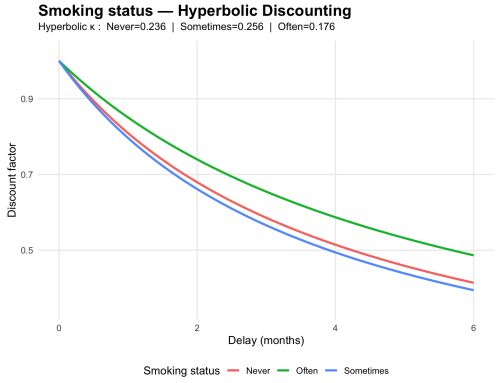
Figure .6: **Appendix Figure D1.** Subgroup-specific discounting (Panels A–C). Each panel compares $D(t)$ under hyperbolic vs exponential fits.



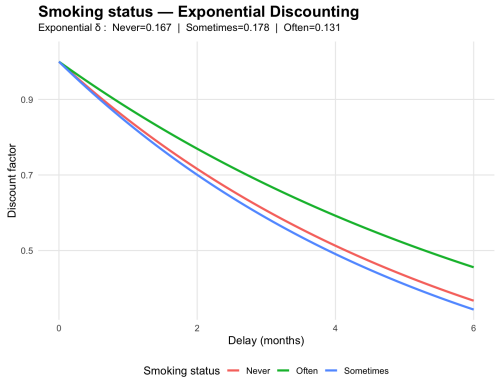
Panel D: Government trust–specific discounting



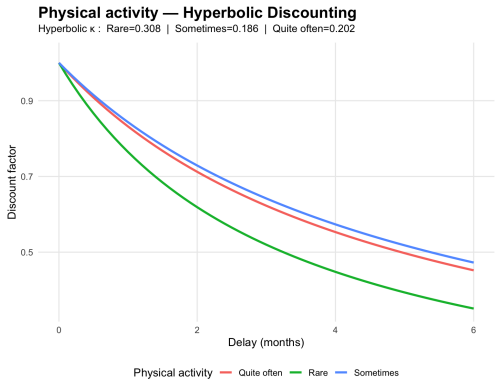
Five levels of government trust.



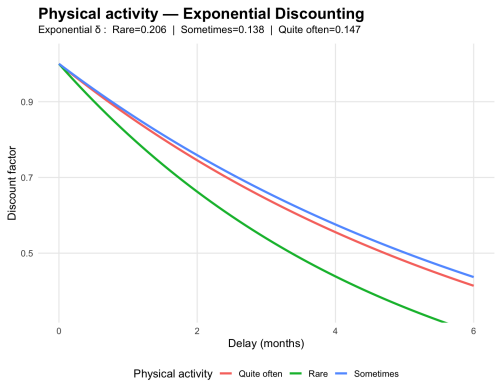
Panel E1: Smoking status–specific discounting



Never, sometimes, often.



Panel E2: Physical activity–specific discounting



Rare, sometimes, quite often.

Figure .7: **Appendix Figure D2.** Subgroup-specific discounting (Panels D–E). Each row shows hyperbolic vs exponential discount functions $D(t)$ for a category.