How Waiting Time Shapes Preventive Health Behavior: Evidence from Vaccination Decisions

Yichao Jin and Dohyeong Kim

Abstract

Timely vaccination is critical for reducing infectious disease risk, yet many individuals delay inmunization even when vaccines are available. This study examines waiting time as a behavioral barrier to preventive health decision-making and evaluates whether institutional trust and medical vuluerability modify responses to delayed protection. We analyzed data from a discrete choice experiment conducted among 1,027 adults in Wuhan, China. Respondents evaluated hypothetical vaccines that varied in efficacy, side effects, waiting time, and monetary incentives. Mixed logit models were used to estimate the behavioral impact of delay and to assess heterogeneity across subgroups.

Longer waiting times significantly reduced the likelihood of vaccine uptake, indicating that delayed protection carries a meaningful behavioral cost. Individuals with lower institutional trust were substantially more sensitive to delay than those with higher trust. Descriptive subgroup summarics also suggested greater aversion to waiting among respondents with chronic medical conditions, although formal interaction tests provided the strongest support for heterogencity by institutional trust. Exploratory subgroup summaries suggested additional heterogencity by smoking frequency, although this pattern was non-linear and is reported as descriptive rather than confirmatory evidence. Supplementary exploratory simulations illustrate that these behavioral responses may also have broader population-level implications.

These findings suggest that waiting time is an important behavioral determinant of vaccination decisions. Reducing administrative delay and strengthening institutional trust may improve the timeliness and equity of preventive health delivery.

Keywords: vaccination, waiting time, preventive health behavior, institutional trust, medical vuluerability, delayed protection

1. Introduction

Vaccination is a cornerstone of preventive health care, but its effectiveness depends not only on whether people accept vaccination, but also on how quickly protection is delivered (Centers for Disease Control and Prevention, 2024). In real-world settings, access to vaccination is often shaped by scheduling frictions, administrative barriers, and limited service capacity (Cantarelli et al., 2024; Liu et al., 2024). These delays may do more than postpone protection. By imposing immediate inconvenience and deferring health benefits, waiting time may discourage uptake itself (Cantarelli et al., 2024). Vaccine delay can therefore be understood not simply as a logistical problem in service delivery, but as a behavioral barrier to preventive care (Centers for Disease Control and Prevention, 2024; Cantarelli et al., 2024; Liu et al., 2024).

Behavioral responses to delay are unlikely to be uniform across individuals (Truong et al., 2022; Walsh et al., 2020). Waiting for protection requires tolerating uncertainty, inconvenience, and a period of continued vulnerability before benefits are realized. Institutional trust may shape confidence that delayed protection is worth pursuing (Ahmad et al., 2022; Truong et al., 2022), while chronic medical condition status and preventive-health routines may influence how burdensome it feels to remain unprotected during the waiting period (Walsh et al., 2020; Parekh et al., 2022; Centers for Disease Control and Prevention, 2024). These characteristics were therefore examined

as theoretically motivated sources of heterogeneity in sensitivity to waiting time, alongside broader subgroup differences across socio-demographic and health-behavior characteristics.

A growing literature suggests that vaccination behavior is influenced by impatience, risk perception, institutional trust, and access-related barriers (Anderson et al., 2023; Robertson et al., 2024; Etowa et al., 2024). However, waiting time is often treated primarily as an administrative friction rather than as a behavioral determinant of preventive decision-making (Lièvre et al., 2024; Tran et al., 2025; Whitaker, 2026). This distinction matters. As an experimentally manipulable service attribute, waiting time may directly affect willingness to vaccinate by altering how individuals evaluate delayed protection. Yet relatively few discrete choice studies have directly examined waiting time in this way, and fewer still have examined how sensitivity to waiting time varies with institutional trust or chronic medical condition status.(Yue et al., 2021; Gong et al., 2020; van der Pol and Cairns, 2001).

To address these gaps, this study examines waiting time as a behavioral barrier to vaccination. We analyze data from a discrete choice experiment administered to 1,027 adults in Wuhan, China, in which waiting time was embedded directly as a vaccine attribute. This design allows us to estimate how delayed protection influences vaccination choices and whether these responses differ across population subgroups. Rather than treating waiting time as a purely operational detail, we examine it as a feature of preventive health delivery that may shape decision-making under uncertainty.

Wuhan provides an informative setting for this analysis because of its high population density, early pandemic experience, and strong public-health visibility. In such a context, delayed protection is likely to be salient to respondents, making it possible to observe how trust, perceived vulnerability, and health-related routines shape responses to waiting. Although the magnitude of these responses may vary across settings, the underlying processes are likely to be relevant more broadly, particularly in contexts where institutional trust plays an important role in preventive health behavior (Sohns et al., 2024; MacDonald et al., 2025).

This study makes three contributions. First, it provides evidence that waiting time is an important behavioral determinant of vaccination decisions. Second, it shows that sensitivity to waiting time varies most clearly by institutional trust, with additional descriptive differences across chronic medical condition status and preventive-health routines. Third, by translating these differences into measures of perceived delay burden, the analysis highlights how the same waiting period may be experienced differently across the population. A brief illustrative epidemic extension is reported in the Supplementary Material.

Together, these findings suggest that waiting time is not merely a logistical feature of vaccine delivery but a meaningful behavioral factor in preventive health decision-making. Understanding how waiting time contributes to vaccine delay may help inform more timely and equitable vaccination strategies.

2. Methods

This study used a discrete choice experiment (DCE) to examine how waiting time influences vaccination decisions and whether responses to delayed protection differ across population subgroups. Waiting time was embedded directly as a vaccine attribute, allowing us to estimate how respondents traded off delayed protection against other vaccine characteristics. In addition to estimating preference heterogeneity, we derived summary measures of time-related valuation from the choice-model coefficients. The main text focuses on the behavioral interpretation of these measures, while additional technical details and validity checks are reported in the online supplementary material.

2.1. Study Design

This study used an online discrete choice experiment (DCE) to examine how waiting time influences vaccination decisions and whether responses to delayed protection differ across population subgroups. Respondents evaluated hypothetical vaccines for a COVID-like disease (CLD), defined as a respiratory infection with transmissibility and severity comparable to COVID-19. This framing was intended to preserve a realistic infectious-disease context while reducing anchoring to a specific epidemic wave, variant, or policy period.

The CLD scenario was used to elicit preferences for delayed protection without tying responses to a single historical phase of the COVID-19 pan-

demic. Similar stated-preference studies have used hypothetical vaccine scenarios to examine vaccination preferences and timing decisions (Louviere et al., 2000; Hensher et al., 2015; Johnson et al., 2013). The survey was administered online in early 2025, when vaccination services were broadly available and respondents were no longer making decisions under the immediate pressures of an acute outbreak.

2.2. Participants and Setting

The survey targeted adults living in Wuhan, China. Sampling quotas for age, gender, and district were used to approximate the demographic composition of the adult population. Eligibility criteria required respondents to be aged 18 years or older, currently reside in Wuhan, and complete all survey modules. Standard attention and data-quality checks were applied before analysis. The final analytic sample consisted of 1,027 respondents. Additional information on sample composition and comparison with Wuhan Census benchmarks is provided in Appendix B. Although the sample slightly overrepresents more highly educated respondents, post-stratification weighting yielded substantively similar results to the unweighted analyses.

Wuhan provides an informative setting for studying responses to delayed protection because of its early pandemic experience, strong public-health visibility, and high salience of vaccination-related decisions. These features make it possible to examine how institutional trust, perceived vulnerability, and preventive-health routines may shape responses to waiting time in a

context where infectious disease risk is readily understood.

2.3. DCE Attributes and Choice Tasks

Each vaccine profile was defined by five attributes: waiting time (0–6 months), vaccine efficacy, expected side effects, vaccine origin, and cash incentives. These attributes were selected to capture key features of vaccination decisions while allowing respondents to evaluate trade-offs between delayed protection and other vaccine characteristics.

Each respondent completed six choice tasks. In each task, respondents chose between two hypothetical vaccine alternatives or an opt-out option. An efficient fractional-factorial design was used to achieve attribute balance and support identification of main effects.

Prior to the main survey, the instrument was pilot-tested with 60 respondents to assess clarity, comprehension, and cognitive burden. Pilot responses informed the priors used in the efficient design algorithm and indicated that task complexity was manageable for the target population. Additional details on attribute definitions, example choice tasks, pilot-based instrument development, and design diagnostics are provided in the online supplementary material.

2.4. Statistical Analysis

We estimated mixed logit models to account for repeated choices and unobserved heterogeneity in vaccination preferences. These models were used to estimate the behavioral impact of waiting time on vaccine choice and to

assess whether sensitivity to delayed protection differed across subgroups defined by demographic characteristics, health behaviors, chronic medical conditions, and institutional trust.

To summarize time-related valuation, we also derived exponential discounting (δ), quasi-hyperbolic present bias (κ), and marginal willingness-to-accept (MWTA) for waiting time from the estimated choice-model coefficients. These measures were used as summary indicators of the perceived burden of delayed protection and to compare responses across subgroups.

All analyses were conducted in R using the `mlogit` and `gmnl` packages. Full model specifications, formal derivations, robustness analyses, epidemic-model details, and supplementary figures are provided in the online supplementary material.

3. Results

3.1. Main Model Estimates

Table 1 presents estimates from the conditional logit, multinomial logit, and mixed logit models. To facilitate comparison across attributes, coefficients were standardized to represent the change in utility associated with a one-standard-deviation change in each attribute.

Across all specifications, waiting time was negatively associated with vaccine uptake. Side effects showed a less stable pattern: they were negatively associated with uptake in the MNL model with alternative-specific constants ($\beta = -0.082$, $p < 0.01$), but this effect was attenuated and became non-

significant in the mixed logit specification. This may reflect substantial heterogeneity in concerns about side effects across respondents, which is better captured in the mixed logit model. By contrast, the negative effect of waiting time remained robust across all models. Because coefficient magnitudes are not directly comparable across specifications due to model-specific utility scales, we use the mixed logit results for substantive interpretation. That specification provided the best fit and captured heterogeneity in responses to waiting time; all subsequent discounting and subgroup analyses are therefore based on the mixed logit model.

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

	Conditional logit	MNL (ASCs)	Mixed logit
Waiting time (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 waiting time (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. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

3.2. Discounting Profiles

Figure 1 presents the estimated discounting profiles from the exponential and hyperbolic models fitted to the observed valuation points. Both curves begin at full value at zero delay and decline monotonically as waiting time increases. The exponential model yielded an estimated discount factor of $\delta = 0.160$, whereas the hyperbolic model yielded $\kappa = 0.225$. The hyperbolic curve showed a sharper initial decline over the first several months, indicating stronger short-run sensitivity to delayed protection.

These estimates suggest that respondents placed disproportionate weight on immediacy when evaluating vaccination. In other words, the behavioral cost of waiting time was not linear across the delay horizon: shorter delays near the present carried especially large behavioral consequences relative to

equal delays further in the future. Additional subgroup-specific discounting estimates are reported in the online supplementary material.

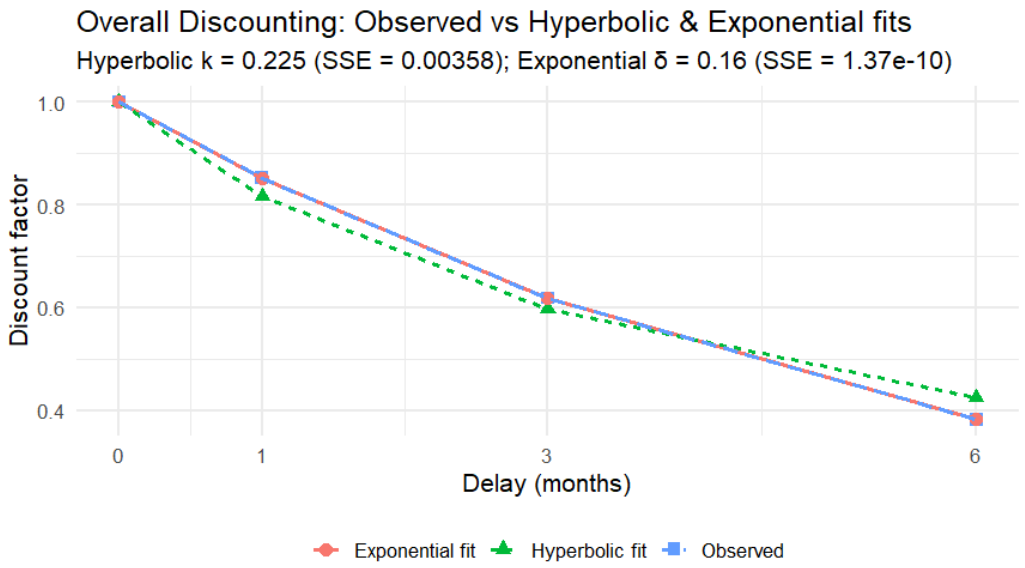

Figure 1: Comparison of observed discounting with hyperbolic and exponential fits.

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.

3.3. Subgroup Variation in Responses to Waiting Time

Responses to waiting time varied across demographic, behavioral, health-related, and institutional subgroups. Figure 2 presents subgroup-specific hyperbolic discount parameters (κ) as descriptive summaries. Higher values indicate stronger present-oriented preferences and greater sensitivity to delayed protection. As shown in the figure, the perceived burden of waiting time was not evenly distributed across the sample, with notable variation across trust,

education, residence, health status, and preventive-health routines. Not all subgroup patterns were monotonic. For smoking, occasional smokers appeared more delay-sensitive than both frequent smokers and never-smokers. As these results are descriptive, they should not be interpreted as formal between-group differences without interaction tests.

Because visual subgroup differences do not by themselves establish statistically significant between-group heterogeneity, we also estimated formal interaction tests for selected prespecified contrasts. Table 2 reports these results. The tests provided evidence of heterogeneity in responses to waiting time by institutional trust, residence, selected education contrasts, and physical activity. In particular, respondents with lower institutional trust, urban respondents, and those with primary-school education were more sensitive to waiting time than their respective reference groups. The contrast between graduates and the college-educated reference group was only marginally significant. By contrast, formal interaction tests did not support statistically significant differences by chronic medical condition status or gender. These results suggest that heterogeneity in responses to waiting time is socially patterned, but not all subgroup differences observed descriptively are supported equally strongly in the current data.

Taken together, these findings suggest that responses to waiting time are heterogeneous, but that the strongest formal evidence concerns variation by institutional trust. Detailed subgroup-specific estimates of delay coefficients and derived discounting parameters are reported in the online supplementary

material.

Table 2: Formal interaction tests for selected subgroup differences in waiting-time sensitivity

Interaction	Comparison group	Interaction coefficient	p-value	Significance
WaitTime × Trust	**Low vs High trust**	−0.069	**0.035**	**
WaitTime × Chronic condition	Yes vs No condition	−0.039	0.433	n.s.
WaitTime × Residence	**Urban vs Rural**	−0.068	**0.029**	**
WaitTime × Education	**Primary school vs College**	−0.126	**0.015**	**
WaitTime × Education	Graduated vs College	−0.111	0.075	*
WaitTime × Physical activity	**Rare vs Sometimes/Quite often**	−0.116	**0.021**	**
WaitTime × Gender	Male vs Female	0.018	0.553	n.s.

Notes: Entries report interaction terms between waiting time and subgroup indicators from the discrete choice model. Negative coefficients indicate greater sensitivity to waiting time in the comparison group relative to the reference group, assuming a negative main effect of waiting time on vaccine choice. $^{*}p < 0.10$, $^{**}p < 0.05$. n.s. = not statistically significant.

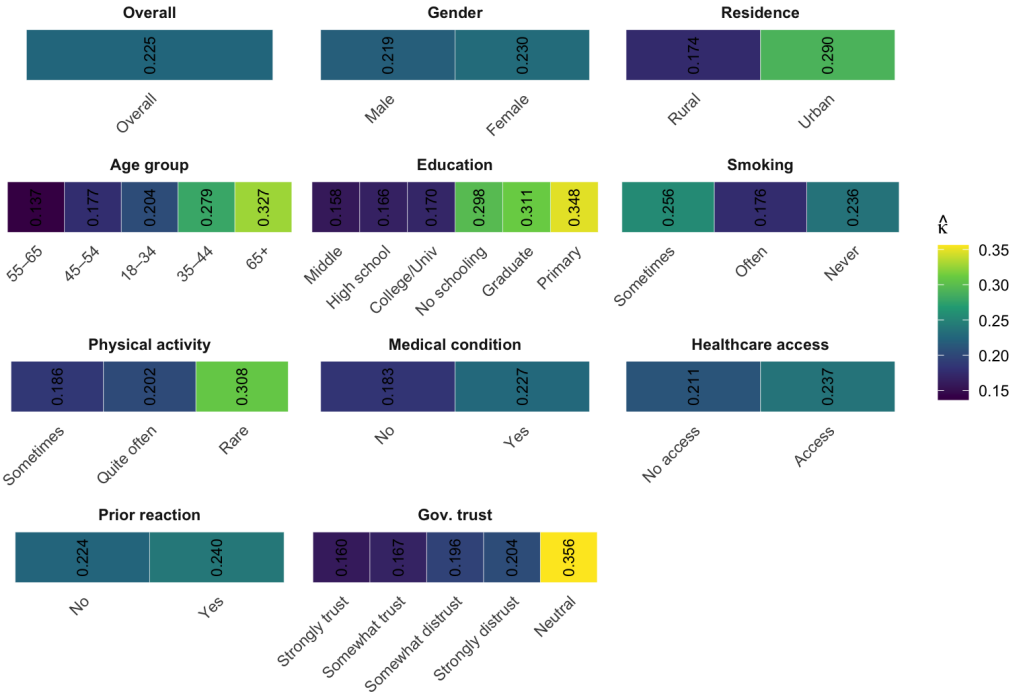

Figure 2: Subgroup variation in hyperbolic discount parameters (κ). Higher values indicate stronger present-oriented preferences (greater impatience toward waiting time). These estimates are descriptive summaries; formal tests of between-group differences are reported in Table 2.

3.4. Perceived Delay Burden

We further summarized the behavioral cost of waiting time using marginal willingness-to-accept (MWTA), which expresses the compensation respondents would require to tolerate an additional month of waiting. Across the full sample, respondents required approximately 45–56 RMB per month of delay, indicating that waiting time imposed a meaningful perceived burden on vaccination decisions.

MWTA estimates also revealed substantial heterogeneity across subgroups. Respondents with lower institutional trust, lower education, and less regular preventive-health routines generally required greater compensation to accept additional waiting, consistent with subgroup differences observed in the discounting parameters. Descriptive subgroup summaries also suggested higher compensation among respondents with chronic medical conditions. For example, respondents with low institutional trust required considerably more compensation for delay than those with high trust. These patterns suggest that the same waiting time may be experienced quite differently across the population.

For brevity, subgroup-specific MWTA estimates and related policy-translation figures are reported in the online supplementary material.

3.5. Exploratory Population-Level Extension

As a brief exploratory extension, we mapped estimated behavioral responses to waiting time into a behaviorally augmented SEIR framework to

illustrate possible population-level implications of delayed uptake. Under selected scenarios, greater sensitivity to waiting time was associated with slower effective vaccination uptake and less favorable epidemic trajectories relative to a supply-only benchmark. Full model equations, calibration procedures, and extended simulation results are provided in the online supplementary material.

4. Discussion

This study examined how waiting time influences vaccination decisions in a hypothetical COVID-like disease setting and whether responses to delayed protection differ across population subgroups. Three main findings emerged. First, longer waiting time substantially reduced willingness to vaccinate, indicating that delayed protection functions as a meaningful behavioral barrier in preventive health decision-making. Second, responses to waiting time were not uniform across the population. Individuals with lower institutional trust were more sensitive to delayed protection, while descriptive subgroup summaries also suggested greater sensitivity among respondents with chronic medical conditions; however, this latter difference was not supported by formal interaction tests. Third, these behavioral patterns were also reflected in discounting-based and monetary summary measures, indicating that the same period of waiting time may be experienced differently across groups.

4.1. Waiting Time as a Behavioral Barrier to Vaccination

The present findings add to a growing literature showing that vaccination decisions are shaped not only by perceived efficacy and side effects, but also by how individuals evaluate the timing of protection (van der Pol and Cairns, 2001; Attema and Brouwer, 2013; Attema et al., 2018). In this study, waiting time was embedded directly as an experimentally manipulated vaccine attribute, allowing us to estimate how delayed protection affects stated vaccination choices. The results suggest that even relatively short delays can carry substantial behavioral weight, consistent with evidence that near-term frictions often have disproportionate effects on preventive health behavior (Brewer et al., 2017; Johnson et al., 2013; Kong et al., 2025).

This interpretation helps clarify why *vaccine delay* persists even when vaccines are available. Delayed access is not experienced merely as an administrative inconvenience. Rather, waiting time appears to influence how respondents weigh immediate burdens against future protection, especially under uncertainty. In this sense, the results are consistent with prior work showing that present-oriented decision-making can shape vaccination timing and other preventive choices (Laibson, 1997; O'Donoghue and Rabin, 1999; Lièvre et al., 2024; Tran et al., 2025). At the same time, the current findings suggest that these behavioral responses are closely tied to the context of health protection, rather than reflecting a single, context-free trait.

4.2. Institutional Trust, Social Patterning, and Health Equity

Institutional trust emerged as the most consistently supported moderator of responses to waiting time. In both the descriptive subgroup estimates and the formal interaction tests, respondents with lower trust were more sensitive to delayed protection than those with higher trust. This pattern is consistent with prior research linking trust to vaccine acceptance, health communication, and adherence to public-health recommendations (Brewer et al., 2017; Betsch et al., 2018). Our findings suggest that institutional trust may function as a psychological buffer against administrative friction. For lower-trust individuals, waiting time may be experienced not simply as delay, but as heightened uncertainty about whether protection will be delivered reliably, thereby amplifying its negative association with vaccine uptake. Under these conditions, the behavioral burden of waiting may be greater, increasing the likelihood of real-world *vaccine delay* among populations that are already less confident in public-health systems.

The interaction results also suggest that responses to waiting time are socially patterned more broadly. Urban respondents were more sensitive to waiting time than rural respondents, and respondents with primary-school education were more delay-sensitive than the college-educated reference group. Evidence for a difference between graduates and the college-educated reference group was weaker and only marginally significant, while gender differences were not statistically significant. Formal interaction tests also indicated significant heterogeneity by physical activity: respondents reporting

rare physical activity were more sensitive to waiting time than those reporting sometimes or quite often engaging in physical activity. By contrast, smoking-related heterogeneity appeared more descriptive and non-monotonic, with occasional smokers appearing more delay-sensitive than frequent smokers. These findings suggest that responses to delayed protection may also be linked to broader preventive-health routines, with less regular physical activity associated with greater sensitivity to waiting time. Taken together, the results indicate that the behavioral consequences of delayed protection are not evenly distributed across the population and may vary systematically with social position and preventive-health routines.

By contrast, the evidence for health-related vulnerability was more limited. Respondents with chronic medical conditions appeared descriptively more sensitive to delayed protection in subgroup-specific estimates, suggesting that waiting time may carry greater perceived cost among those facing elevated health risk. However, the formal interaction test for chronic condition status was not statistically significant. This indicates that, although the direction of the pattern is consistent with a vulnerability-based interpretation, the present data do not provide equally strong statistical support for chronic condition status as a moderator of waiting-time sensitivity.

Taken together, these findings have implications for health equity. Although waiting time may appear to be a neutral administrative feature of service delivery, its consequences are unlikely to be evenly distributed. For individuals with lower institutional trust or other characteristics associated

with greater sensitivity to waiting time, delayed protection may carry higher perceived and practical costs, including prolonged exposure to infectious risk, greater uncertainty, and disruption to work or caregiving responsibilities. From this perspective, waiting time can be understood as a structural barrier that may contribute to unequal patterns of *vaccine delay*, particularly when health systems rely on uniform scheduling arrangements that do not account for differences in trust, social position, or available resources.

4.3. Implications for Preventive Health Delivery

These findings have several implications for preventive health delivery. First, they suggest that reducing waiting time may improve vaccination uptake even when vaccines are widely available, because delays in service delivery can function as behavioral barriers rather than merely logistical frictions. Second, the results indicate that these behavioral costs are not distributed evenly across the population. The strongest formal evidence of heterogeneity concerns institutional trust, suggesting that individuals with lower trust may be especially discouraged by delayed protection. In practice, this implies that timely access, predictable scheduling, and clear communication may be particularly important in populations that are more sensitive to waiting.

More broadly, the findings highlight that vaccination programs should be evaluated not only in terms of supply availability, but also in terms of how service delivery shapes behavior. Delays may reduce uptake even when capacity exists, and this effect may be amplified when trust in institutions

is limited. From a public-health perspective, these results underscore the importance of designing preventive services that minimize delay and reduce uncertainty around when protection will be received.

The monetary summary measures reported in this study are useful because they translate the burden of waiting time into a more interpretable metric. However, the central implication is behavioral rather than purely economic: the same delay may be experienced differently across groups, and those differences may matter for equitable preventive-health delivery.

A brief exploratory simulation, reported in the Supplementary Material, further illustrates that behavioral responses to waiting time could matter beyond the individual level by shifting effective uptake later under selected scenarios.

4.4. Practical Implications

These findings suggest that interventions to improve vaccination uptake should address not only vaccine availability, but also the organization of access. Reducing waiting time may be especially important for individuals who are more sensitive to delayed protection, particularly those with lower institutional trust, while descriptive subgroup patterns suggest potential vulnerability among respondents with chronic medical conditions. In practice, this implies that timely scheduling, transparent communication about expected wait times, and predictable access procedures may help reduce behavioral barriers to vaccination.

The results also have implications for health equity. If the burden of waiting time is greater for socially or medically vulnerable groups, then uniform delivery arrangements may unintentionally widen disparities in uptake. Strategies such as reliable appointment systems, clear queueing procedures, and targeted efforts to reduce uncertainty may therefore be especially important in populations facing greater barriers to timely protection.

More broadly, these findings suggest that service design should be understood as part of preventive health intervention design. Programs that make access more timely, transparent, and predictable may help reduce real-world *vaccine delay* and support more equitable vaccination uptake.

4.5. Limitations

Several limitations should be noted. First, as with all stated-preference studies, hypothetical bias may affect the absolute magnitude of estimated valuations. Although the survey incorporated realistic attribute ranges, repeated choice tasks, an opt-out option, and pilot-based refinement, the results should be interpreted primarily as evidence on relative behavioral patterns rather than exact population-level parameters (Louviere et al., 2000; Johnson et al., 2013; Hensher et al., 2015). In addition, the DCE captures decisions in a relatively deliberative setting and may not fully reflect the affective intensity of real outbreak conditions. If waiting time increases anxiety or perceived exposure during actual outbreaks, our estimates may understate the psychological burden associated with real-world *vaccine delay*.

Second, the study was conducted in Wuhan, a setting with unusually high salience of infectious disease and vaccination, which may influence the magnitude of observed responses. Third, chronic medical conditions were self-reported rather than clinically verified. Finally, the epidemic-modeling component is exploratory and should not be interpreted as a full policy evaluation.

5. Conclusion

This study shows that waiting time is an important behavioral determinant of vaccination decisions. Longer waits reduced willingness to vaccinate, and this effect was strongest among respondents with lower institutional trust, while descriptive subgroup summaries suggested additional variation by chronic medical condition status. These findings suggest that *vaccine delay* is shaped not only by access constraints, but also by how individuals perceive and respond to delayed protection.

From a behavioral medicine perspective, the results highlight the importance of service design in preventive health behavior. Reducing waiting time, improving the predictability of access, and strengthening institutional trust may help support more timely and equitable vaccination uptake. More broadly, these findings suggest that behavioral responses to delayed protection should be considered when designing preventive health programs and evaluating barriers to timely care.

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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Online Supplementary Material

How Waiting Time Shapes Preventive Health Behavior: Evidence from Vaccination Decisions

This document provides supplementary materials referenced in the main manuscript, including instrument materials and validity checks, sample benchmarking, model estimation details and derivations, subgroup-specific plots, trade-off computations, and an exploratory epidemic simulation.

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 behavior, (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 behavioral coherence of the responses.

A.1 Dominance Behavior

Dominance tests assess whether respondents ever chose an alternative that was strictly dominated on all attributes. As shown in Table 1, only 1.8% of respondents violated dominance at least once, a rate that is low by the standards commonly used in DCE research. This pattern suggests that most 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 1 indicates that ANA was 0% for waiting time, 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 1: Dominance behavior and attribute non-attendance (ANA)

Check	**Definition**	**Result (%)**
Dominance rate	Share selecting a dominated alternative	1.8
ANA: Waiting time	Choices invariant to waiting-time 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 1 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.

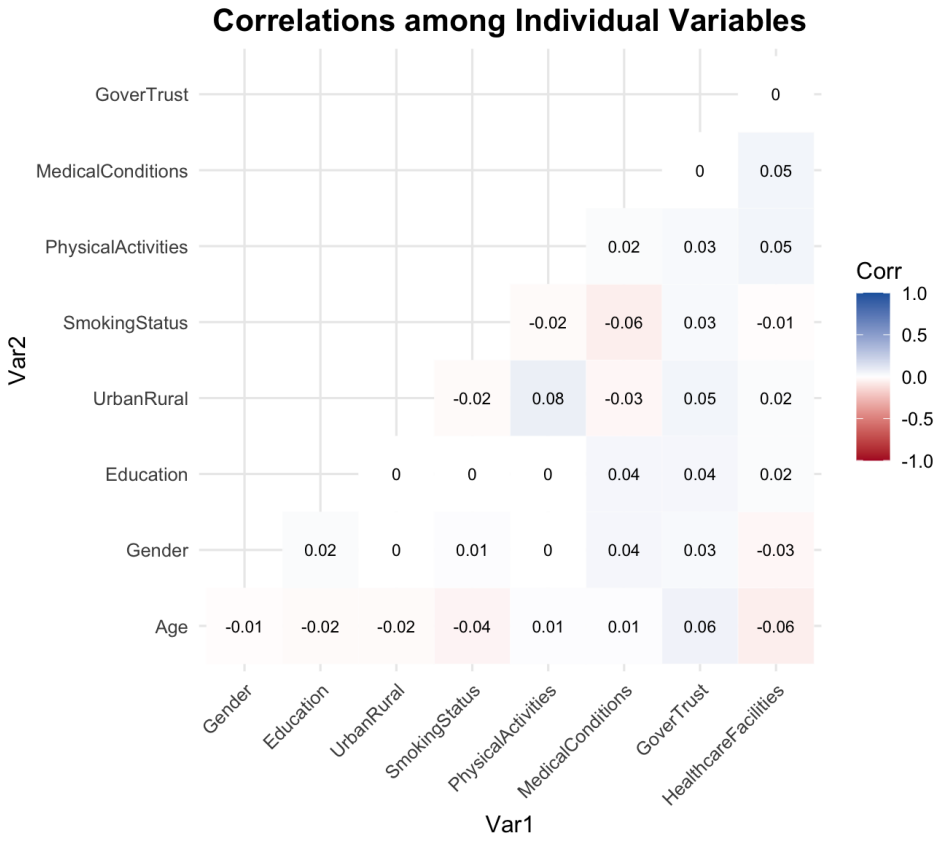


Figure 1: Correlation matrix of individual-level covariates. Darker colours indicate stronger correlations. All coefficients are below 0.10, confirming negligible multicollinearity.

A.5 Example Choice Task

Figure 2 provides an example of the choice task presented to respondents. Each task featured two hypothetical vaccine profiles varying across five attributes—waiting time, origin, efficacy, side-effect severity, and cash incentives—and an opt-out alternative. Attribute descriptions appeared at the top of the screen. For example, efficacy was defined behaviorally 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 waiting time (0 vs. 1 month), side-effect severity (fatigue for one week vs. fever lasting two days), and incentives (800 CNY vs. 200 CNY).

Figure 2: 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 waiting time, 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 (Wuhan Municipal Bureau of Statistics, 2021). Sampling quotas were used to align the sample with the city's adult population on gender, age, and district of residence. As shown in Table 2, 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 2: 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 (Wuhan Municipal Bureau of Statistics, 2021). 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 overrepresentation of 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. Additional Model Estimation Details

This appendix provides additional detail on model estimation and diagnostic procedures. Throughout, **waiting time** refers to the experimentally manipulated attribute in the discrete choice experiment, whereas *vaccine delay* refers to the corresponding behavioral consequence in real-world uptake.

C1. Utility Specification

Vaccination choices were modeled within a random-utility framework. Let respondent i choose among alternatives j in choice task t. Indirect utility is specified as

$$U_{ijt} = \beta_0 + \beta_1 \,\text{WaitingTime}_{ijt} + \beta_2 \,\text{VaccineEfficacy}_{ijt} + \beta_3 \,\text{SideEffects}_{ijt} + \beta_4 \,\text{CashIncentives}_{ijt} + \beta_5 \,\text{VaccineOrigin}_{ijt} + \beta_6 \,\text{ASC}_{\text{opt-out},ijt} + \varepsilon_{ijt}, \tag{C1}$$

where ε_{ijt} is an idiosyncratic error term. In the main models, continuous attributes were entered in standardized form to facilitate comparison across coefficients, while additional transformations were used where necessary to recover per-month **waiting-time** effects for subsequent discounting and MWTA calculations.

For comparison, three model classes were estimated in the main analysis: conditional logit, multinomial logit with alternative-specific constants (ASCs), and mixed logit. The conditional and multinomial logit models provide useful baselines, whereas the mixed logit specification was preferred for substantive interpretation because it accommodates repeated choices by respondent and allows for unobserved preference heterogeneity.

C2. Mixed-Logit Estimation and Identification

The preferred specification was a mixed logit model estimated on the respondent-level panel structure of the data. In this model, the coefficient on **waiting time** was specified as random in order to capture heterogeneity in sensitivity to delayed protection across respondents. The general mixed-logit representation can be written as

$$U_{ijt} = \beta_i' X_{ijt} + \varepsilon_{ijt}, \tag{C2}$$

where β_i varies across individuals according to a prespecified distribution and X_{ijt} con-

tains the observed vaccine attributes. Estimation was implemented using simulated maximum likelihood with respondent-level panel identification.

The mixed logit model was chosen as the preferred specification for three reasons. First, it provided the best fit among the candidate models based on the log-likelihood and Akaike Information Criterion reported in the main text. Second, the estimated standard deviation of the random **waiting-time** coefficient was statistically significant, indicating meaningful heterogeneity in responses to delayed protection. Third, the mixed-logit framework is better suited than fixed-coefficient logit models to represent repeated stated choices from the same respondent.

Although coefficient magnitudes differed across conditional logit, multinomial logit, and mixed logit specifications, these values should not be interpreted as directly comparable effect sizes because utility scale is model-specific. For this reason, all subsequent discounting, MWTA, and subgroup analyses reported in the main text were based on the preferred mixed-logit specification rather than on cross-model comparisons of coefficient magnitude.

C3. Subgroup Estimation and Multiplicity

To examine heterogeneity in responses to **waiting time**, subgroup-specific mixed-logit models were estimated for demographic, behavioral, health-related, and institutional categories. These subgroup estimates were used as descriptive summaries of variation in **waiting-time** sensitivity and to recover subgroup-specific discounting parameters reported in the supplementary subgroup tables and figures.

Because subgroup estimation involves multiple comparisons, significance levels for subgroup-specific **waiting-time** coefficients were adjusted using the Benjamini–Hochberg false-discovery rate (FDR) procedure at $q = 0.10$. Holm–Bonferroni corrections were also examined and yielded substantively similar conclusions. Importantly, these subgroup-specific models were intended primarily as descriptive summaries. Formal tests of between-group differences were conducted separately using interaction terms, as reported in the main text.

Accordingly, the empirical strategy distinguishes between two forms of heterogeneity analysis:

1. **Subgroup-specific estimation**, which summarizes within-group patterns in **waiting-time** sensitivity; and

2. **Formal interaction tests**, which provide inferential evidence on whether responses to **waiting time** differ significantly between selected groups.

C4. Additional Diagnostics

Several additional diagnostics were conducted to assess the robustness of the preferred specification.

First, model-comparison statistics favored the mixed logit model over the conditional and multinomial logit alternatives. In particular, the mixed-logit specification improved fit while also capturing heterogeneity in **waiting-time** sensitivity.

Second, the negative association between **waiting time** and vaccine uptake was stable across all main specifications. By contrast, some other attributes were less stable across models. For example, side effects were statistically significant in the multinomial logit model with ASCs but attenuated and became non-significant in the mixed-logit specification. This pattern suggests that concern about side effects may vary substantially across respondents and may be partly absorbed by the unobserved preference heterogeneity captured in the more flexible mixed-logit model.

Third, alternative specifications and diagnostic checks were examined to assess response quality and model dependence. These included re-estimation after excluding potential speeders, checks for dominance violations and attribute non-attendance, and sensitivity analyses for subgroup coding choices. Across these alternatives, the sign and substantive interpretation of the **waiting-time** effect remained unchanged.

Taken together, these diagnostics support the use of the mixed-logit specification as the

primary model for substantive interpretation while reinforcing the robustness of the central finding that longer **waiting time** reduces willingness to vaccinate.

Appendix D. Additional Subgroup Results

This section reports detailed subgroup-specific estimates of **waiting-time** sensitivity and derived discounting parameters. These results are provided as descriptive summaries to complement the subgroup figure presented in the main text. Significance markers in the tables below indicate whether the waiting-time coefficient differs from zero within each subgroup; they do not by themselves imply statistically significant differences between subgroups. Formal interaction tests of between-group differences are reported in the main text and in the supplementary interaction-test section.

Table 3: Subgroup-specific estimates of waiting-time sensitivity and derived discounting parameters

Group	n	$\beta_{\text{waiting time}}$ (std)	$\beta_{\text{waiting time}}$ (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

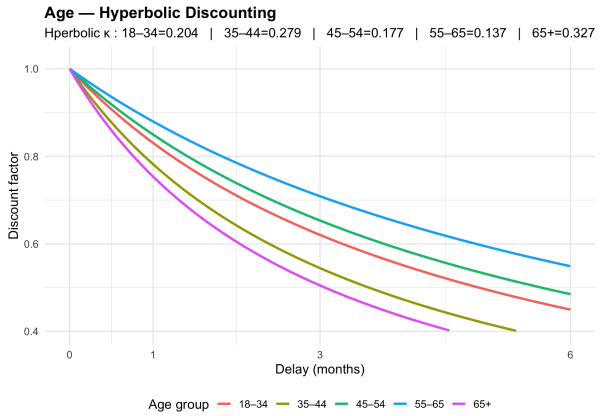
Notes: Standard errors are shown in parentheses. n indicates the number of respondents in each subgroup. Significance markers indicate whether the subgroup-specific waiting-time coefficient differs from zero; they do not by themselves imply statistically significant differences between subgroups. p-values were adjusted using the Benjamini–Hochberg false-discovery rate ($q = 0.10$); Holm–Bonferroni corrections yielded similar conclusions. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Subgroup-specific estimates of waiting-time sensitivity and derived discounting parameters (continued)

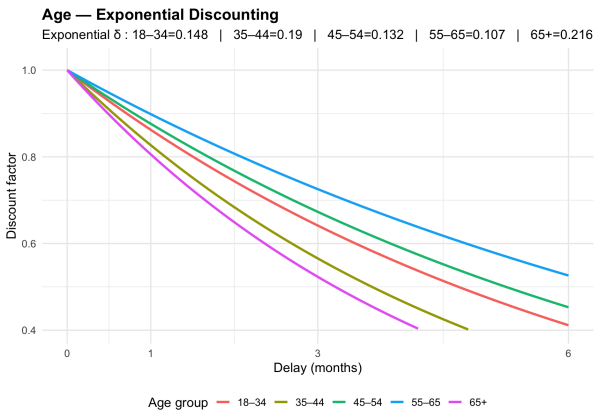
Group	n	$\beta_{\text{waiting time}}$ (std)	$\beta_{\text{waiting time}}$ (per mo)	κ / δ
Smoking status				
Never	311	-0.367^{***} (0.043)	-0.167^{***} (0.020)	0.236 / 0.167
Sometimes	402	-0.392^{***} (0.039)	-0.178^{***} (0.018)	0.256 / 0.178
Often	314	-0.290^{***} (0.044)	-0.131^{***} (0.020)	0.176 / 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
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

Additional Subgroup Discounting Plots

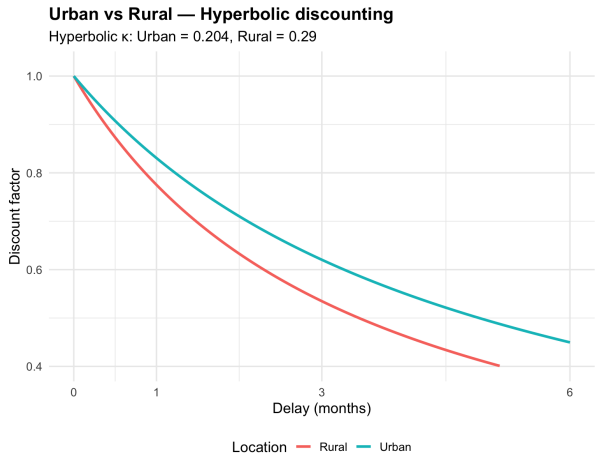
Figures 3 and 4 provide subgroup-specific discounting profiles for selected categories. These plots compare observed discounting with fitted hyperbolic and exponential curves and are intended as descriptive summaries of how responses to **waiting time** vary across subgroups.



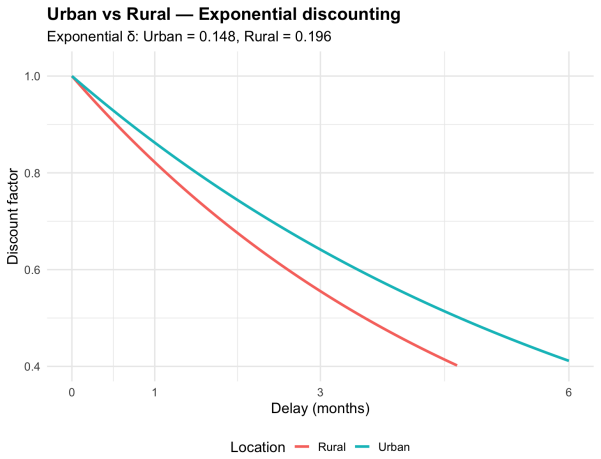
Panel A: Age-specific discounting. Five age groups (18–34, 35–44, 45–54, 55–65, 65+).



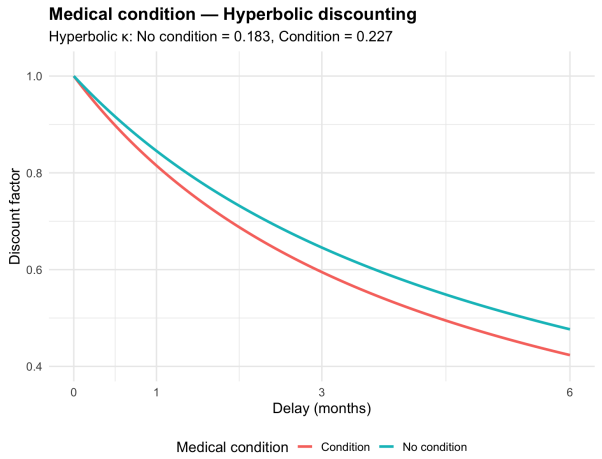
Five age groups (18–34, 35–44, 45–54, 55–65, 65+).



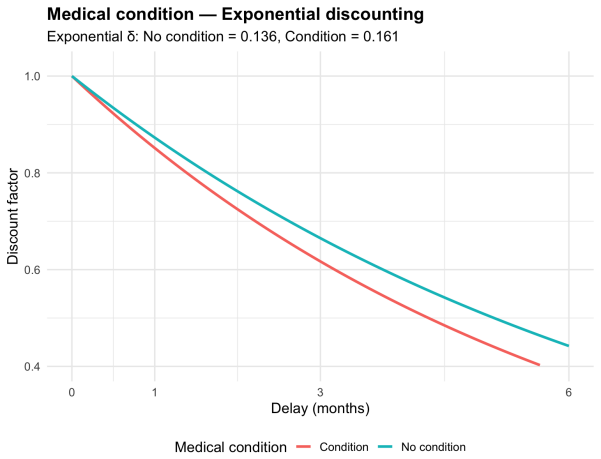
Panel B: Residence-specific discounting.



Urban versus rural respondents.

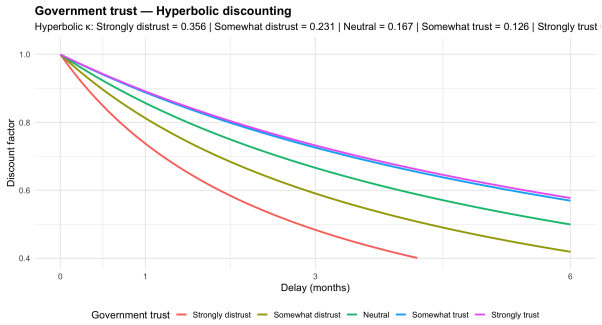


Panel C: Medical-condition-specific discounting.

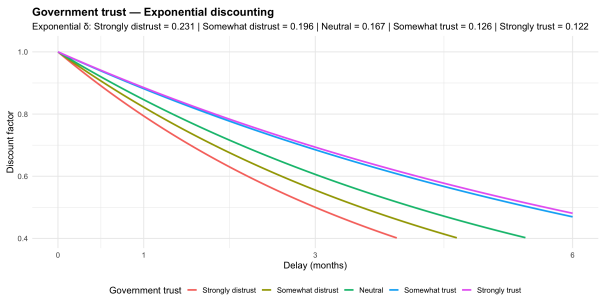


Individuals with versus without medical conditions.

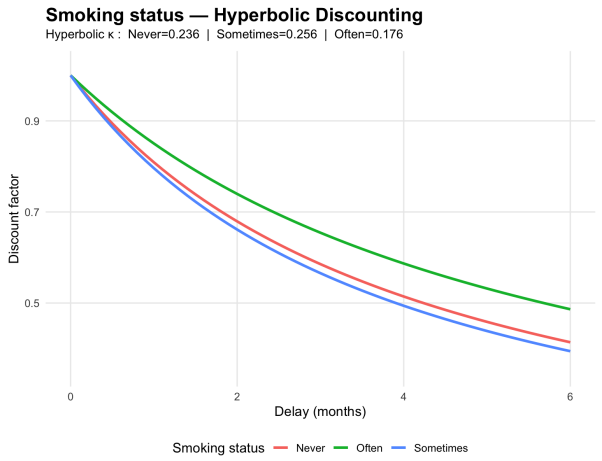
Figure 3: **Supplementary Figure S1.** Subgroup-specific discounting profiles (Panels A–C). Each panel compares observed discounting with fitted hyperbolic and exponential curves. These figures are provided as descriptive summaries of subgroup variation in responses to **waiting time**.



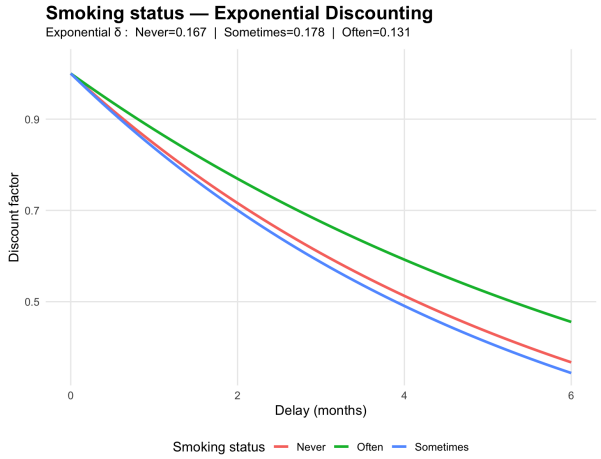
Panel D: Institutional-trust-specific discounting.



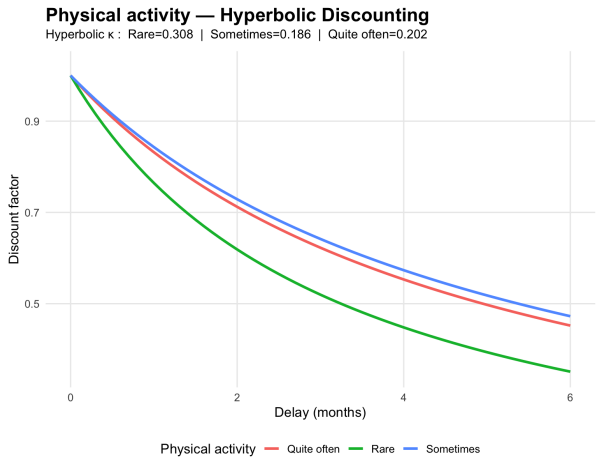
Five levels of institutional trust.



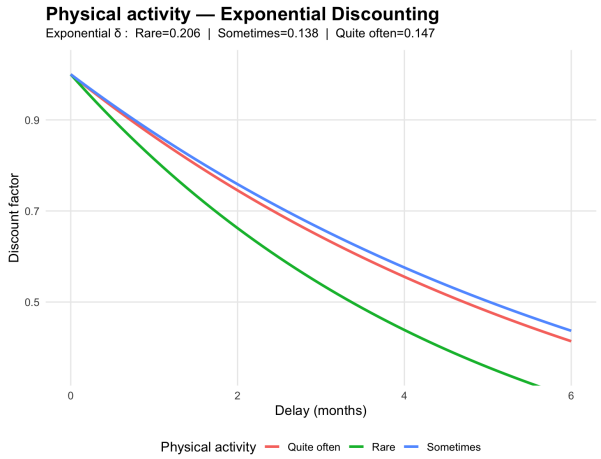
Panel E1: Smoking-status-specific discounting.



Never, sometimes, often.



Panel E2: Physical-activity-specific discounting.



Rare, sometimes, quite often.

Figure 4: **Supplementary Figure S2.** Subgroup-specific discounting profiles (Panels D–E). Each row shows hyperbolic versus exponential discount functions for a subgroup category. These figures are descriptive and are intended to complement the formal interaction tests reported in the main text and elsewhere in the supplementary material.

Appendix E. MWTA Derivation for Waiting Time

This appendix derives the marginal willingness-to-accept (MWTA) for one additional month of **waiting time** using the preferred mixed-logit specification. Throughout, **waiting time** refers to the experimentally manipulated attribute in the discrete choice experiment, whereas *vaccine delay* refers to the corresponding behavioral consequence in real-world uptake.

E1. Definition

MWTA represents the amount of monetary compensation required to offset the utility loss associated with one additional month of **waiting time**. Let $\beta_{\text{waiting time (per month)}}$ denote the mixed-logit coefficient for one month of waiting, and let β_{cash} denote the coefficient on cash incentives. Then the general expression for MWTA is

$$\text{MWTA} = -\frac{\beta_{\text{waiting time (per month)}}}{\beta_{\text{cash (RMB)}}}. \tag{E1}$$

This quantity is expressed in RMB and can be interpreted as the compensation required, on average, to make respondents indifferent to one additional month of waiting.

E2. Conversion from the standardized cash coefficient

In the preferred mixed-logit model, the cash-incentive attribute was entered in standardized form. Let $\beta_{\text{cash (std)}}$ denote the estimated coefficient on the standardized cash variable, and let SD(Cash Incentives) denote the sample standard deviation of the original cash-incentive variable measured in RMB. The corresponding coefficient in RMB units is therefore

$$\beta_{\text{cash (RMB)}} = \frac{\beta_{\text{cash (std)}}}{\text{SD(Cash Incentives)}}. \tag{E2}$$

Substituting Equation (E2) into Equation (E1) yields

$$\text{MWTA} = -\frac{\beta_{\text{waiting time (per month)}}}{\beta_{\text{cash (std)}}/\text{SD(Cash Incentives)}} = -\frac{\beta_{\text{waiting time (per month)}} \times \text{SD(Cash Incentives)}}{\beta_{\text{cash (std)}}}. \tag{E3}$$

Equation (E3) is the expression used in the main analysis. It ensures that MWTA is reported in RMB even though the cash coefficient was estimated using a standardized regressor.

E3. Application to the preferred mixed-logit model

For the preferred mixed-logit specification, the waiting-time effect is first expressed in per-month units and then combined with the standardized cash coefficient using Equation (E3). Thus, the overall MWTA is calculated as

$$\text{MWTA}_{\text{overall}} = -\frac{\hat{\beta}_{\text{waiting time (per month)}} \times \text{SD(Cash Incentives)}}{\hat{\beta}_{\text{cash (std)}}}. \tag{E4}$$

The same procedure is applied to subgroup-specific estimates, replacing the overall waiting-time coefficient with the relevant subgroup-specific value. As a result, subgroup differences in MWTA reflect variation in behavioral responses to **waiting time** evaluated against a common monetary scale.

E4. Interpretation

MWTA provides a monetary summary of the perceived burden of **waiting time**. Larger MWTA values indicate that respondents require greater compensation to tolerate an additional month of waiting, implying stronger aversion to delayed protection. In the main text, these values are used to translate the behavioral cost of waiting into an interpretable metric for comparing overall and subgroup-specific responses.

Importantly, MWTA should be interpreted as a preference-based summary measure

rather than as a market price or a direct welfare estimate. Its primary purpose is to express the utility cost of delayed protection in a common monetary unit that facilitates comparison across groups.

Appendix F. Formal Interaction Tests

Formal interaction tests were conducted to evaluate whether responses to **waiting time** differed significantly across selected prespecified subgroups. These analyses complement the descriptive subgroup-specific estimates reported in the previous section by providing direct tests of between-group differences in waiting-time sensitivity.

The interaction model augmented the preferred discrete choice specification by including cross-product terms between **waiting time** and subgroup indicators. In general form, the utility of alternative j for respondent i in choice task t can be written as

$$U_{ijt} = \beta_0 + \beta_1 \,\mathrm{WaitingTime}_{ijt} + \sum_{k=2}^{K} \beta_k X_{k,ijt} + \sum_{m=1}^{M} \gamma_m \big(\mathrm{WaitingTime}_{ijt} \times Z_{im}\big) + \varepsilon_{ijt},$$

where $X_{k,ijt}$ denotes the remaining vaccine attributes, Z_{im} denotes subgroup indicators, and γ_m captures whether the behavioral response to **waiting time** differs significantly across groups. A negative interaction coefficient indicates greater sensitivity to **waiting time** in the comparison group relative to the reference group, assuming a negative main effect of waiting time on vaccine choice.

The main manuscript reports the results of the selected interaction tests used for substantive interpretation. In brief, the strongest formal evidence of heterogeneity was observed for institutional trust, with additional evidence for selected residence- and education-based contrasts. By contrast, interaction terms for chronic medical conditions and gender were not statistically significant. These results should therefore be interpreted together with the descriptive subgroup-specific estimates reported in the previous section.

Accordingly, the supplementary material does not repeat the full interaction-test table from the main text. Instead, this section documents the role of the interaction analyses within the broader empirical strategy: subgroup-specific estimates are used as descriptive summaries, whereas the formal interaction models provide the inferential basis for claims about statistically significant between-group heterogeneity in responses to **waiting time**.

Appendix G. Exploratory Epidemic Simulation (SEIR Extension)

This appendix presents an exploratory population-level extension linking behavioral responses to **waiting time** to epidemic dynamics. The purpose of this extension is illustrative: it shows how heterogeneity in responses to delayed protection may affect the timing of effective vaccine uptake and, in turn, outbreak trajectories. This appendix is not intended as a full forecasting exercise or a complete policy evaluation.

Model structure

We used a behaviorally augmented susceptible–exposed–infectious–removed (SEIR) framework. Let S_t, E_t, I_t, and R_t denote the susceptible, exposed, infectious, and removed populations at time t, with total population size $N = S_t + E_t + I_t + R_t$. Vaccination reduces the susceptible population through an effective vaccination rate that depends on both delivery capacity and behavioral acceptance. The model is given by

$$\frac{dS_t}{dt} = -\beta \frac{S_t I_t}{N} - v_{\text{eff}}(t) S_t,$$

$$\frac{dE_t}{dt} = \beta \frac{S_t I_t}{N} - \sigma E_t,$$

$$\frac{dI_t}{dt} = \sigma E_t - \gamma I_t,$$

$$\frac{dR_t}{dt} = \gamma I_t + v_{\text{eff}}(t) S_t,$$

where β is the transmission rate, σ is the progression rate from exposed to infectious status, and γ is the recovery rate.

Behavioral vaccination function

To incorporate behavioral responses to delayed protection, the effective vaccination rate is defined as

$$v_{\text{eff}}(t) = v_{\text{cap}}(t) \times P_t,$$

where $v_{\text{cap}}(t)$ denotes the maximum operational vaccination capacity at time t, and P_t denotes the probability of vaccine uptake implied by the estimated choice model under the relevant **waiting time** scenario.

In the benchmark scenario, uptake is constrained only by delivery capacity, such that $P_t = 1$. In the behavioral-response scenarios, $P_t < 1$ and varies according to the estimated delay sensitivity recovered from the discrete choice experiment. For subgroup-specific simulations, P_t was adjusted using subgroup-specific response parameters so that greater sensitivity to **waiting time** translated into slower effective uptake.

Calibration and simulation scenarios

The simulation was calibrated to illustrate how behavioral responses to **waiting time** may shift vaccination later in the epidemic curve. Epidemiological parameters were chosen to generate plausible outbreak dynamics for a COVID-like respiratory infection, while the be-

havioral component was informed by the estimated discounting parameters and subgroup-specific delay sensitivity reported in the main analysis.

We compared three classes of scenarios:

1. **Supply-only benchmark:** vaccine uptake is determined entirely by operational capacity, with no behavioral penalty from **waiting time**.

2. **Average behavioral-response scenario:** effective uptake is reduced according to the full-sample response to delayed protection.

3. **Subgroup behavioral-response scenarios:** effective uptake varies according to subgroup-specific sensitivity to **waiting time**, allowing illustration of heterogeneity in epidemic consequences.

The primary outcome was the cumulative attack rate. We also examined representative infection trajectories to illustrate how behavioral responses to delayed protection may alter the timing and magnitude of infections over the course of an outbreak.

Interpretation

This extension should be interpreted as a behavioral illustration rather than a structural epidemic forecast. The goal is to demonstrate that **waiting time**, estimated at the individual level as a behavioral barrier to vaccination, may also have population-level implications when it slows effective uptake during the early growth phase of an outbreak. In this sense, *vaccine delay* can arise not only from logistical constraints but also from behavioral responses to delayed protection.

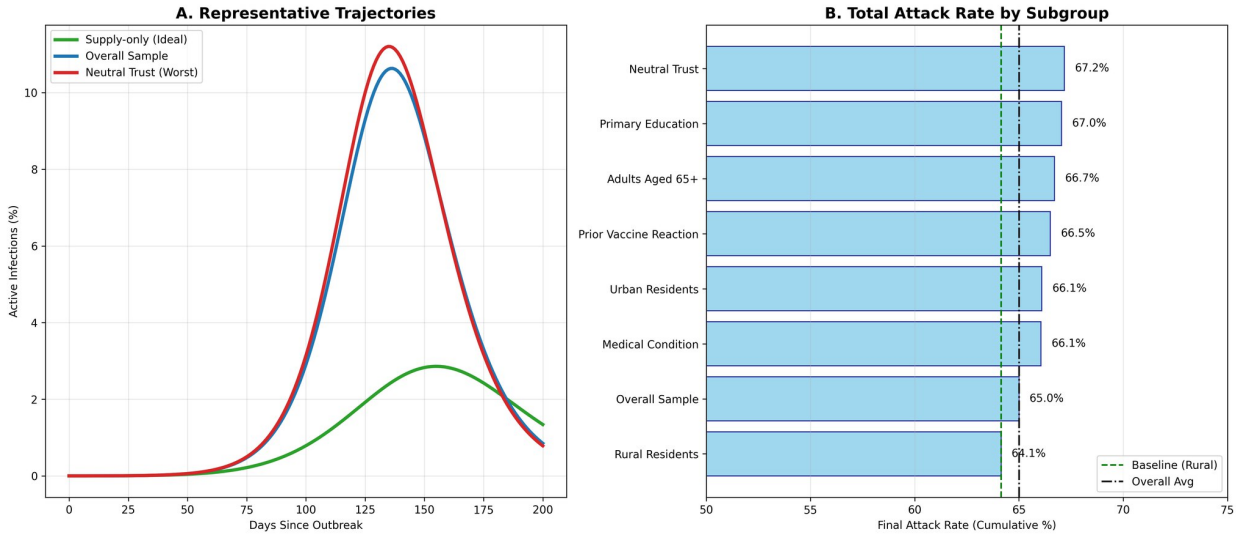


Figure 5: **Appendix Figure F1.** Exploratory SEIR-based simulation. **Panel A** shows representative infection trajectories under a supply-only benchmark and under behavioral-response scenarios. **Panel B** summarizes cumulative attack rates across selected subgroups, illustrating how stronger sensitivity to delayed protection can shift effective uptake later in the outbreak and increase cumulative infections.

Note. This SEIR extension is included to illustrate how estimated behavioral responses to **waiting time** may translate into population-level epidemic consequences. Full scenario assumptions, additional robustness checks, and further calibration details can be provided if needed.

References

Wuhan Municipal Bureau of Statistics (2021). *Wuhan Statistical Yearbook 2021*. China Statistics Press, Wuhan, China.