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Coverage Without Consensus: An Evolutionary Game-Theoretic Analysis of Punjab's 2025 HPV Vaccination Campaign

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ABSTRACT

The September 2025 Human Papillomavirus (HPV) immunization drive in Punjab marked the country's largest-ever vaccination campaign for a single disease, since the polio eradication drive. This study reports three simultaneous outcomes: provincial coverage of 81 percent of the eligible cohort against a target of 8.54 million girls (93 percent against an operational target of 7.27 million girls), while 2.74 million households refused the vaccines; the level of coverage varied considerably across districts, ranging from 73 percent in Rajanpur to 91 percent in Okara. The campaign accomplished these results without spending any money on formal enforcement, at an incremental administrative overhead of roughly Rs. 0.85 per girl vaccinated (a marginal cost figure that excludes vaccine and cold-chain costs borne by Gavi). The school-based delivery channel underperformed, in contrast to the community outreach program, which overperformed. To formalise these dynamics, we construct a three-player evolutionary game between households, the state, and misinformation actors and fit it to the 2025 campaign outcomes. The parameterized model identifies conditions under which an interior equilibrium can be locally stable. We then use the parameterized model to simulate four counterfactual policy scenarios. Findings show that contact intensity rather than demand-side persuasion is the dominant lever for coverage.

Keywords: HPV vaccination; Evolutionary game theory; Vaccine hesitancy; Pakistan; Public health policy

1. INTRODUCTION

Cervical cancer is the third leading cause of mortality among Pakistani women, and it is responsible for almost 5000 new cases of cancer each year (Bray et al. 2024; Bruni et al., 2023; de Martel et al., 2017; Furqan, Rahim & Haider, 2025). Most of the disease burden occurs in women of reproductive and middle age and is caused by chronic infection with oncogenic types of the human papillomavirus, mainly HPV-16 and HPV-18 Loya et al. (2016). The case for prevention is unusually compelling: For girls, one dose of bivalent HPV vaccine is highly effective, long-lasting and, as recommended by the World Health

Organization in their recently published single-dose schedule for HPV vaccines in LMICs, economically viable WHO (2022).

The introduction of HPV vaccine into the national immunization schedule was thus long overdue and impactful, as it was implemented through a campaign conducted from 15 September to 4 October 2025 in Pakistan. The campaign involved 4 jurisdictions: Punjab, Sindh, Islamabad Capital Territory (ICT) and Azad Jammu and Kashmir (AJK) with planned expansion to KPK in 2026 and Balochistan and Gilgit-Baltistan (GB) in 2027, funded by Gavi, the Vaccine Alliance, with technical support from the World Health Organisation (WHO) and UNICEF according to UNICEF Pakistan (2025). The administered vaccine is a bivalent vaccine called Cecolin, WHO (2024) that was purchased at a unit cost of approximately USD 0.55 per dose, under the Gavi co-financing mechanism Gavi (2024).

There are multiple aspects of the outcome of the Punjab campaign which are impressive and which call out for the present analysis. The campaign was successful in hitting the operational target of 7.27 million girls, with 93 percent coverage achieved, and the broader eligible cohort of 8.54 million girls in the target age band, with 81 percent coverage achieved. This difference, or the "operational gap" of around 1.27 million girls who were eligible but not covered by the campaign, is before accounting for refusal, and includes girls that were not targeted by this round of the campaign. Second, the overall success was accompanied with 2.74 million school and community-level refusals, and significant district-level differences with coverage ranging from 73 percent in Rajanpur to 91 percent in Okara. The campaign was successful in achieving the required coverage without the need for any legal enforcement (enforcement expenditure equal to zero), through a mix of school-based delivery, community-based outreach and persuasion.

Third, and in contrast to the school-led template developed for the Rwanda campaign (LaMontagne et al. 2011), the drive in Punjab had a lower school channel than expected (49 percent of 5.17 million), and a higher community channel (202 percent of 2.09 million). The overall figure conceals a massive real-time reconfiguration of the delivery model with community outreach absorbing significant volume that the school channel could not provide. The administrative data cannot fully distinguish the mechanisms behind the community channel's 202 percent overperformance against its planned target. Possible explanations include: (a) the community planning target was underestimated relative to the actual out-of-school population; (b) girls missed in the school phase were reassigned to community records; (c) community workers revisited initial refusers, generating additional contact events; (d) school refusals were subsequently converted through home visits recorded under the community channel; or (e) there were reporting overlaps between channels in the MIS.

This association of high coverage, significant volumes of refusal, and channel performance that is reversed, pose an interesting question that descriptive analysis cannot provide a full answer to: what are the conditions under which such an equilibrium occurs, and what does it mean for the design of the 2026 and 2027 phases?

Two questions follow for the relaunch. First, if the community channel's overperformance in Punjab was driven by revisitation of initial refusers, will provinces with lower Lady Health Worker density be able to replicate the same contact intensity? Second, if the acceptance rate among contacted households (71 percent in Punjab) reflects a particular misinformation environment, will it hold in provinces with different religious and social-media dynamics or does the saddle structure of the equilibrium mean that even modest differences in the misinformation parameter push outcomes toward a different attractor?

This study makes four contributions to existing literature, it captures the cost structure, channel composition, and variation in district-level coverage of the Punjab 2025 campaign from administrative data from the Punjab EPI. Furthermore, it constructs a three-player evolutionary game between households, the state, and misinformation actors and identifies the conditions for the coverage refusal pattern seen in the Punjabi data in the interior equilibria. Additionally, it employs the parameterized model and district variation to simulate multiple scenarios for relaunch of the 2026/2027 expansion.

The rest of the research is organized as follows. Section 2 reviews existing literature. The institutional context, the administrative data, the cost analysis, and the district-level variation are presented in Section 3. In Section 4, the three-player evolutionary game is developed. The equilibrium conditions of the model are derived in Section 5. The model is parameterized to campaign data and scenarios are simulated in Section 6. In Section 7, policy implications for the relaunch are discussed. Section 8 concludes the study.

2. LITERATURE REVIEW

The economic case for HPV vaccination in LMICs has been demonstrated in a large body of literature. Levin et al. (2014) show that HPV vaccination can be highly cost effective even with conservative estimates of vaccine cost, coverage and loss of protection. This shift from double dose to single dose administration by WHO's Strategic Advisory Group of Experts in 2022 made cost-effectiveness ratios much better and increased the group of countries for which the vaccine became financially feasible.

However, the introduction of vaccination drives has remained inconsistent. Rwanda's school-based programme was launched in 2011 and covered more than 93 per cent in the first year and is often regarded as a good model for LMIC implementation (Binagwaho et al., 2012). However, in 2009, the Andhra Pradesh and Gujarat pilot studies in India failed, due to accusations of poor consent procedures and adverse events, showing that clinical safety records, particularly of high quality, can be politically sensitive if governance of implementation is challenged (Larson et al., 2010).

The experiences outlined above are the bases for the 2025 introduction of Pakistan. The campaign's emphasis on the school-based delivery is modelled on the Rwandan precedent; pre-launch consultation with the Council of Islamic Ideology and religious leaders at the provincial level demonstrates sensitivity to the Indian context. What is novel and analytically interesting, however, is the de facto re-balancing toward community outreach that occurred during implementation, suggesting that it was a planning assumption that was not necessarily a binding operational plan.

2.1 Vaccine hesitancy

The most prominent model in the public health literature to explain vaccine hesitancy is the 3Cs model developed by the WHO SAGE Working Group: Confidence (trust in vaccine safety, effectiveness, and the health system offering it), Complacency (perceived risk of the disease), and Convenience (physical and economic accessibility) (MacDonald & SAGE Working Group, 2015). Larson et al. (2014) add a population-level measure of trust: the Vaccine Confidence Index, developed in response to the gap documented by Larson et al. (2011).

For HPV hesitancy specifically, a number of consistent predictors of HPV vaccine refusal have been identified through empirical studies: lack of knowledge about cervical cancer as a distinct disease, fears about sexual consequences of HPV vaccination for pre-adolescent girls, distrust of health care programs funded by foreign donors, and engagement with HPV vaccination misinformation on social media. Before the 2025 campaign, significant gaps were observed on these dimensions in studies conducted in Pakistan. Furqan et al. (2025) and Luwen et al. (2025) found less than 20 per cent of the women had heard of HPV and even less about the HPV vaccine.

The 2025 campaign experience brings in a modern note: rejection was also confined to certain districts, the lowest coverage districts were clustered in the South of Punjab (Rajanpur, Multan, Khanewal, Bahawalnagar), whilst a smaller cluster of urban underperformers included Lahore (82 percent) – the most literate district in the province. Urban underperformance was blamed on the spread of false information via social media from influencers who have high urban followings, while religious opposition came in during the campaign.

2.2 Game theory model

Decisions about vaccinating are strategically interdependent: A person's payoff from vaccination is a function of the percentage of people in the community who are vaccinated, based on the concept of herd immunity, and the percentage of people in the community who are misinformed.

Bauch and Earn (2004) offer a basic treatment, which demonstrates that the perceived risk of the vaccine has to be greater than the perceived risk of the disease for people to volunteer to be vaccinated, but there is no internalization of the externality of herd immunity. It shows that households are the strategic actors, while the state and anti-vaccine actors act as exogenous shifts in the relative risk r, which may be manipulated by media or advocacy. This study, on the other hand, adds two other strategic populations, the state and misinformation actors with explicit payoff functions. This naturalises the misinformation environment and the policy response, providing strategic feedback which is not included in the Bauch–Earn framework. Moreover, Bauch and Earn (2004) define a Nash equilibrium while the present study introduces replicator dynamics that describe the trajectory of the proportions of strategies over time and can be used to characterize the saddle structure at the interior equilibrium. Thirdly, Bauch and Earn's infection probability π_p is endogenous by solving an SIR epidemic model with basic reproductive ratio R_0, whereas this paper uses the linear approximation of perceived disease-risk reduction, $\rho(x) = x$. The downside of the simplification is that the model does not capture the key result of Bauch and Earn because the epidemic feedback that is responsible for this result is muted; instead the model emphasizes the strategic interaction among three populations at levels of observed vaccination coverage.

Galvani, Reluga and Chapman (2007) extend this to influenza and show that public subsidies and mandates can fill the gap. Kabir and Tanimoto (2019) use evolutionary game theory to model the dynamics of vaccination decisions where people change their strategies based on the observed payoffs in their social neighbourhood. The present study incorporates government and misinformation actors as strategic actors with explicit payoff functions. This extension is needed to endogenize misinformation; vaccination acceptance becomes a function of the nature of misinformation, in addition to household costs. The manuscript also develops a closed-form interior equilibrium and analytical comparative statics in place of numerical simulations.

The existing literature leaves two gaps that this paper addresses. First, no prior evolutionary theory game theoretic vaccination model incorporates misinformation actors as a distinct strategic population with their own payoff function; existing models treat misinformation as an exogenous environmental parameter rather than the endogenous outcome of a strategic actor's optimisation. Sohag et al. (2026) are a recent exception in treating disinformation as strategically chosen, but do so in a differential-game setting rather than as a population-level evolutionary process parameterized to observed campaign coverage. Second, while Kuga, Tanimoto and Jusup (2019) show in a multi-player setting that subsidy can increase vaccination uptake, their model does not parameterize real administrative data. This study addresses these gaps by using district-level data to drive model findings and incorporating the role of misinformation in the model.

3. EVOLUTIONARY GAME MODEL

This section develops the theoretical framework. We model the campaign environment as an evolutionary game with three populations of players, each with a binary strategy set, and we derive the replicator dynamics governing the evolution of strategy proportions over time.

3.1 Players and Strategies

There are three populations:

Population H (Households): Each household with an eligible girl chooses between strategies V (vaccinate) and R (refuse). Let $x \in [0,1]$ denote the proportion of households playing V.

Population G (Government / EPI): The state chooses between P (persuasion-only) and E (conditional enforcement). Let $y \in [0,1]$ denote the proportion of state effort allocated to E. In the 2025 campaign, y

= 0 by observation. Here y is not exactly the government it represents the individuals operating in the government such as enforcement officers and bureaucracy.

Population M (Misinformation actors): Social media influencers and ideologically motivated opposition choose between A (active anti-vaccine messaging) and S (silent). Let $z \in [0,1]$ denote the proportion playing A.

3.2 Payoffs

Household payoffs

The payoff has four terms: a social-proof benefit $b \cdot \rho(x)$ rising with peer coverage ($\rho(x) = x$ captures descriptive social norms, not herd immunity; Larson et al., 2015), a private vaccination cost c_v, a misinformation disutility $\gamma \cdot z$ (Kabir and Tanimoto, 2019), and an enforcement compliance gain $\delta \cdot y$ (Tyran and Feld, 2006).

$$\pi\_H(V) = b \cdot \rho(x) - c\_v - \gamma \cdot z + \delta \cdot y$$

where b is the perceived health benefit, c_v is the direct cost of vaccinating, γ is the responsiveness of household perceptions to misinformation prevalence z, and δ captures the additional payoff from compliance under enforcement. The payoff from refusing is:

$$\pi\_H(R) = w - \delta \cdot y \cdot \sigma$$

where w is a baseline payoff to refusal and $\sigma \in [0,1]$ is the probability that an enforcement regime detects and sanctions a refuser.

Enforcement enters both payoffs; the linear $\gamma \cdot z$ specification follows Rossini et al. (2024).

State payoffs. Enforcement yields

$$\pi\_G(E) = \alpha \cdot x - c\_E - \lambda \cdot (1-x)$$

Persuasion yields:

$$\pi\_G(P) = \alpha \cdot x - c\_P - \mu \cdot z$$

Misinformation actor payoffs.

$$\pi\_M(A) = \theta \cdot (1-x) - c\_A - \nu \cdot y$$

Silence yields baseline w_M.

The payoff function of a misinformation actor is modelled after Herasimenka et al. (2022) in which the earnings of anti-vaccination actors are seen rising with the size of the vaccine hesitant audience due to potential profit from donations, information products, and ads. The cost term in the model is meant to account for investments in the organization and infrastructure needed to carry out misinformation campaigns, and the enforcement term is meant to capture the disruptive effects of measures that make it more costly for people to actively misinform, like deplatforming. The benefits of inaction are positive because there are other sources of income or alternative fallback networks that enable actors to keep on receiving some benefits even if their main channel is cut off.The actor is active when the net return $\theta\cdot(1-x) - c_A - \nu\cdot y$ exceeds the silence payoff w_M.

Table 1. Parameter glossary

Symbol	Interpretation	Sign / Range
b	Perceived health benefit per unit of disease-risk reduction	$b > 0$
c_v	Private cost of vaccinating (time, travel, anxiety)	$c_v > 0$
w	Baseline payoff to refusing (autonomy, conformity)	$w \geq 0$
γ	Responsiveness of household perceptions to misinformation prevalence	$\gamma > 0$
δ	Compliance gain to vaccinating under enforcement	$\delta > 0$
σ	Detection / sanction probability under enforcement	$\sigma \in [0,1]$

α	Political / health value of one unit of coverage (cancels in payoff difference)	$\alpha > 0$
c_P, c_E	Unit costs of persuasion and enforcement	$c_P, c_E > 0$
λ	Political cost of coercion that scales with refusal share $(1-x)$	$\lambda > 0$
μ	Erosion of persuasion effectiveness by misinformation prevalence	$\mu > 0$
θ	Social-influence return to anti-vaccine messaging (scales with $1-x$)	$\theta > 0$
c_A	Unit cost of producing and distributing misinformation	$c_A > 0$
w_M	Baseline payoff to misinformation actor silence	$w_M \geq 0$
ν	Deterrent effect of enforcement on misinformation activity	$\nu > 0$

Source: Author's own calculations

3.3 Replicator Dynamics

The proportion of each population playing its first strategy evolves according to the replicator equation. For the three populations this yields the system:

$$dx/dt = x(1-x)[\pi\_H(V) - \pi\_H(R)]$$

$$dy/dt = y(1-y)[\pi\_G(E) - \pi\_G(P)]$$

$$dz/dt = z(1-z)[\pi\_M(A) - \pi\_M(S)]$$

The corner equilibrium of analytical interest, given the 2025 campaign's observed configuration, is one where $y^* = 0$, $z^* > 0$, and x^* is interior.

4. ADMINISTRATIVE DATA ANALYSIS

The data used in this paper were drawn from the Punjab EPI Campaign Management Information System (MIS), which records contact events at the district and channel level during the campaign period of 15 September to 4 October 2025. District-level figures represent the sum of school and community channel records within each district. Refusals are recorded as general refusals and do not represent individual girls or households. School and community vaccinations are recorded separately within the MIS and should be mutually exclusive by design; however, the 202 percent overperformance of the community channel against its planned target suggests that some girls initially counted in school channel targets may have ultimately been vaccinated through community routes and recorded there. District-wise details of the campaign are reported in tables A1-A3 of the appendix.

The small numerical difference between operational vaccinations (6,748,717) and eligible-cohort vaccinations (6,878,311) reflects the inclusion of some girls vaccinated outside the formal school/community channel targets in the eligible-cohort count. District coverage rates are reported against the eligible cohort denominator (8,536,154) throughout this study unless otherwise stated. The data shows two different target concepts and the difference is significant. The operational target of the campaign was 7,267,350 girls, which would be the target population during 15 September to 4 October 2025. Eligible cohort was the total estimated population of girls in the age group 9-14 across the province of Punjab, which is 8,536,154. The gap between the two (1.27 million girls) is the eligible population not targeted in this round (usually out-of-school girls and girls in transit, and eligibility-population residuals not accounted for in microplanning). The campaign was delivered to 6,747,717 girls in comparison to 7,267,350 operational target (93 percent), and 6,878,311 girls in comparison to 8,536,154 eligible cohort target (81 percent) girls. Table 2 summarises the indicators.

Table 2. Coverage and delivery summary, Punjab 2025 HPV campaign (15 Sep – 4 Oct 2025)

Indicator	Target	Covered	Covered %
Schools mobilized	127,688	—	—
School vaccinations	5,172,606	2,518,752	49%
Community vaccinations	2,094,744	4,228,965	202%
Total vaccinations (operational target)	**7,267,350**	**6,747,717**	**93%**
Eligible cohort (full population)	**8,536,154**	**6,878,311**	**81%**
Refusals recorded	2,739,740	—	—

Source: EPI

Table 2 shows that the campaign was a significant operational success, with 81 percent of eligible cohort coverage, although lower than the 90 percent targets of Rwanda. Four distinct denominators appear in the data and must be kept separate to avoid confusion. First, the eligible cohort is 8,536,154 girls aged 9–14 in Punjab. Second, the operational target is 7,267,350 girls (the microplanning estimate of reachable girls); the gap of approximately 1.27 million between these two figures represents out-of-school girls, girls in transit, and planning residuals not covered in this round. Third, operational vaccinations — girls receiving a dose via the school or community channel — total 6,747,717, giving a 93 percent operational coverage rate. Fourth, eligible-cohort vaccinations total 6,878,311 (which is slightly higher than operational vaccinations because some girls vaccinated outside the formal operational channels are counted in the eligible-cohort figure but not the operational channel totals). Fifth, recorded refusals total 2,739,740 decisions (not necessarily girls; see data note below). The acceptance rate of 71.1 percent is computed as: 6,747,717 / (6,747,717 + 2,739,740) = 6,747,717 / 9,487,457 = 71.1 percent among all contacted decisions. The eligible-cohort coverage of 80.6 percent is computed as: 6,878,311 / 8,536,154 = 80.6 percent. These are different denominators computed from different base figures and must not be blended. A note on refusal measurement is necessary. Total operational vaccinations are 2518752+4228965= 6747717. The EPI MIS records refusals at the level of the contact event — a recorded interaction at which vaccination was declined. This is not necessarily equivalent to a unique girl or unique household. If a community vaccinator revisited a refusing household, the second interaction may generate a second refusal record in the same MIS entry. If a girl refused in the school channel and was later visited at home via the community channel, she may appear as a refusal in both channels. The total of 2.74 million refusal records is therefore an upper bound on the number of unique girls who refused. The paper treats the acceptance rate among contacted decisions (71.1 percent) as the parameterization target for x^*, which is appropriate because x^* models the probability that a contacted household accepts at a given contact event — not the share of unique girls who were ever reached and ultimately accepted.

The underlying acceptance rate of 71 percent of contacted household is a key figure for planning a relaunch because a program that achieved 81 percent coverage of eligible children in the Punjab could generate lower contact intensity and/or a higher refusal rate among those KPK or Balochistan residents under the assumption that marginal household is more refusal-prone than the average household reached in the Punjab: either because fewer children in the marginal household are attending school, or because there is a greater pressure of misinformation or a weaker tendency of health systems to be trusted by those in the marginal household. This is the main policy issue addressed by the evolutionary dynamic game model.

The most notable in Table 2 is that the channel mix is reversed from what was planned. The campaign was structured around a school-led approach: 71 percent of the operational target (5,172,606 girls) was to be reached via mobilized schools, and 29 percent (2,094,744) through community mobilization. This design has been inverted in the actual delivery profile. The school-based delivery covered only 49 per cent of the target, and community outreach delivered 102 per cent of the target to 4,228,965 girls.

The community channel ended up providing 62.7% of recorded vaccinations and taking in an estimated 1.7 million doses which the school channel could not reach. There are multiple possibilities which can explain this phenomenon. Firstly, the percentage of enrolled females between 9-14 years could be overestimated in school microplanning, especially for lower middle income and southern Punjab districts where there are significantly lower enrolment rates than the provincial average. Additionally, parents who refused vaccination through schools might have been recontacted by community leaders and convinced to get their daughters vaccinated. Lastly, girls who were not enrolled in schools were probably reached out to by community leaders and persuaded to get vaccinated.

The implications for the relaunch are straightforward and tangible. If the out-of-school situation among girls is worse in KPK, Balochistan, and GB compared to Punjab, then the outreach work will have to be scaled up accordingly. However, the community health worker (LHW) capacity and the door-to-door visitation protocol already in place from the polio programme was crucial for the 2025 Punjab campaign to be successful in its implicit aim of handling and accepting a 2x volume surge in community channels. This surge capacity does not automatically exist in provinces where the LHW network is sparser.

Table 3 summarizes the cost of training in which district cascade training made around 67.1% while monitoring and training costs were 14% and 19% respectively whereas enforcement costs were zero.

Table 3. Reported direct cost composition, Punjab 2025 HPV campaign

Cost Component	Amount (Rs.)	Share of Total
HPV Training	1,116,000	19.0%
District Cascade Training	3,942,000	67.1%
HPV Monitoring	820,000	14.0%
Enforcement	0	0.0%
Total reported	**5,878,000**	**100.0%**

Source: Author's own calculations

Table 4. District coverage rate distribution, Punjab 2025

Statistic (across 36 Punjab districts)	**Value**
Mean coverage rate	80.6%
Median coverage rate	80.5%
Standard deviation	4.4 percentage points
Minimum (Rajanpur)	73%
Maximum (Okara)	91%
Districts below 80%	17 of 36 (47.22%)
Districts at or above 90%	1 of 36 (Okara)

Source: Author's own calculations

Table 4 establishes district level heterogeneity and figure 1 shows that lowest coverage districts are clustered in Southern Punjab. This pattern is consistent with a higher γ (responsiveness to misinformation) in urban areas with greater social media penetration, though we caution that this is a post hoc rationalisation rather than a prediction: the model is parameterized to province-wide aggregates, not district-level data, and γ itself is not independently estimated at the district level. The Lahore-Okara contrast is offered as an illustration of the mechanism the model formalises, not as out-of-sample model validation.

Figure 1: District level coverage

Source: EPI

5. EQUILIBRIUM ANALYSIS

5.1 Payoff Differences

We begin by writing the strategy-payoff differences for each population in a compact reduced form. From Section 4.2, the household payoff difference between vaccinating and refusing is

$$\pi\_H(V) - \pi\_H(R) = b \cdot \rho(x) - c\_v + \delta y - \gamma z - [w - \delta y \sigma]$$

Following the convention in Bauch and Earn (2004) and Kabir and Tanimoto (2019), we adopt the linear specification $\rho(x) = x$ for perceived disease risk reduction, meaning that the perceived health benefit scales linearly with population coverage.

$$f\_H(x, y, z) \equiv \pi\_H(V) - \pi\_H(R) = b \cdot x - (c\_v + w) - \gamma z + \delta(1+\sigma) \cdot y \qquad (1)$$

Similarly, the state's payoff difference between enforcement and persuasion is

$$f\_G(x, y, z) \equiv \pi\_G(E) - \pi\_G(P) = \alpha x - c\_E - \lambda(1-x) - [\alpha x - c\_P - \mu z]$$

which simplifies (the αx terms cancel) to

$$f\_G(x, y, z) = (c\_P - c\_E - \lambda) + \lambda x + \mu z \qquad (2)$$

The cancellation of αx in equation (2) is substantively important: because the state values coverage equally whether achieved through enforcement or persuasion, the choice between the two strategies depends only on their relative costs and on the externalities (the political cost of visible coercion λ and the misinformation drag μ), not on the level of coverage itself.

The misinformation actor's payoff difference is

$$f\_M(x, y, z) \equiv \pi\_M(A) - \pi\_M(S) = \theta(1-x) - c\_A - \nu y - w\_M$$

which we write as

$$\mathbf{f\_M(x, y, z) = (\theta - c\_A - w\_M) - \theta x - \nu y} \qquad \mathbf{(3)}$$

Equations (1)–(3) are the building blocks for everything that follows. The full replicator system from Section 4.3 can now be written compactly as

$$dx/dt = x(1-x) \cdot f\_H(x,y,z)$$

$$dy/dt = y(1-y) \cdot f\_G(x,y,z)$$

$$dz/dt = z(1-z) \cdot f\_M(x,y,z) \qquad (4)$$

5.2 Equilibrium analysis

A rest point of system (4) satisfies dx/dt = dy/dt = dz/dt = 0. Equation 4 shows that each equation vanishes whenever the x,y or z equals 0 or 1, or whenever the corresponding payoff difference is zero.

Table 5 summarises the three corner equilibria together with the boundary equilibrium on which the remainder of the analysis focuses.

Table 5. Equilibria of the replicator system

		Eigen values			
(x,y,z)	**Interpretation**	**λ_x**	**λ_y**	**λ_z**	**Stable at parameterization**
(1,0,0)	Universal voluntary vaccination; no enforcement; no misinformation	−0.50	−0.25	−0.29	Yes
(0,0,1)	Universal refusal; no enforcement; active misinformation	−1.00	−0.45	+0.71*	Yes

(1,1,0)	Universal vaccination under enforcement; misinformation deterred	−1.25	+0.25	−0.59	No
Interior	Mixed equilibrium with y* = 0 (the analytically relevant case)				

Source: Author's own calculations

Both (1,0,0) and (0,0,1) are simultaneously stable under baseline parameterization meaning that the system is bi-stable. This indicates that the system does not drift gradually away from 71 percent acceptance; it tips decisively toward one of two corners.

5.3 The Analytically Relevant Equilibrium

Three observations about the 2025 Punjab campaign emerge: (i) the state spent zero formal enforcement expenditure, or $y = 0$; (ii) acceptance of the campaign was about 71 percent, which is strictly interior, or $x \approx 0.71$; and (iii) misinformation actors were qualitatively active, with $z > 0$. Here z is a latent variable; that is, it is not directly observed in the EPI administrative data. The value $z^* = 0.42$ assumed in the parameterization is based on qualitative evidence of anti-vaccine social media activity during the campaign as opposed to a measurement from the MIS, and as such should be interpreted as directional rather than point estimates. The equilibrium of interest is where is $y^*=0$ (pure persuasion strategy) and x^* and z^* are interior. A note on $y=0$ is in order: this does not necessarily imply that there was no push, no pressure from schools, nor any informal conditionality regarding the campaign. The variable y indicates formal enforcement intensity (factual enforcement sanctions or legal enforcement demands) and $y = 0$ is set based on the observation that there was no enforcement expenditure recorded in the 2025 budget (Table 2). Informal social pressure is represented in the payoff parameters, not the payoffs y.

With $y = 0$, system (4) reduces to a planar (two-dimensional) system in (x, z):

$$dx/dt = x(1-x)\cdot[b\cdot x - (c_v + w) - \gamma z]$$

$$dz/dt = z(1-z)\cdot[(\theta - c_A - w_M) - \theta x] \quad (5)$$

Step 1. Solve $f_M(x, 0, z) = 0$ for x^*.

Setting $f_M = 0$ in (5) and solving for x:

$$(\theta - c_A - w_M) - \theta x^* = 0$$

$$x^* = (\theta - c_A - w_M) / \theta = 1 - (c_A + w_M)/\theta \qquad (6)$$

Equation (6) shows that the acceptance rate at the interior equilibrium depends only on parameters of the misinformation actor's problem: the gross influence return θ and the actor's opportunity cost ($c_A + w_M$). The intuition is that x must adjust to a level at which misinformation actors are indifferent between activity and silence because otherwise z would not be interior.

For x^* to be a valid interior point we require $0 < x^* < 1$, which holds whenever $0 < c_A + w_M < \theta$. That is, the misinformation actor's opportunity cost must be positive but smaller than the maximum influence return.

Step 2. Solve $f_H(x^*, 0, z) = 0$ for z^*.

Substituting $y = 0$ and $x = x^*$ into $f_H(x, y, z) = b\cdot x - (c_v + w) - \gamma z$ and setting equal to zero:

$$b\cdot x^* - (c_v + w) - \gamma z^* = 0$$

$$z^* = [b\cdot x^* - (c_v + w)] / \gamma \qquad (7)$$

For z^* to be interior we require $0 < z^* < 1$, which yields the parameter restriction

$$c_v + w < b\cdot x^* < c_v + w + \gamma$$

The left side inequality says household acceptance at equilibrium must generate enough perceived benefit to outweigh the private cost of vaccinating plus the baseline refusal payoff; this is necessary for any positive uptake to be sustainable. The right-side inequality says misinformation sensitivity γ must be large enough to render z^* a fraction less than one; if γ is too small, even fully active misinformation cannot push household indifference to a vaccinate-favouring equilibrium.

Step 3. Verify $y^* = 0$ is consistent.

The reduction in step 1 assumed $y = 0$. We confirm that $y = 0$ is a rest point by noting that $dy/dt = y(1-y)\cdot f_G(x,y,z)$, which vanishes at $y = 0$ regardless of the value of f_G.

5.4 Stability Analysis via the Jacobian

Local stability of an equilibrium is determined by the eigenvalues of the Jacobian matrix of the right-hand side of system (4) evaluated at the equilibrium. We compute the 3×3 Jacobian at $(x^*, 0, z^*)$ and characterise its eigenvalues.

Step 1. Form the Jacobian.

Let $F(x,y,z) = (F_1, F_2, F_3)$ denote the right-hand side of (4), with $F_1 = x(1-x)f\_H$, $F_2 = y(1-y)f\_G$, $F_3 = z(1-z)f\_M$. Then

$J = \partial F/\partial(x,y,z)$ evaluated at $(x^*, 0, z^*)$

Using the product rule, each diagonal entry takes the form

$$\partial F_i/\partial \xi_i = (1 - 2\xi_i)\cdot f_i + \xi_i(1 - \xi_i)\cdot \partial f_i/\partial \xi_i$$

Off-diagonal entries are simpler: $\partial F_i/\partial \xi_j = \xi_i(1 - \xi_i)\cdot \partial f_i/\partial \xi_j$ for $i \neq j$.

At $(x^*, 0, z^*)$ we have $f\_H = 0$ and $f\_M = 0$ by definition of the equilibrium, so the $(1 - 2\xi_i)\cdot f_i$ terms vanish on rows 1 and 3. The entire row 2 is multiplied by $y(1-y) = 0\cdot 1 = 0$ in the off-diagonals, leaving only the $(1-2y)\cdot f\_G = f\_G(x^*, 0, z^*)$ diagonal term on row 2.

Step 2.

Using equations (1)–(3) and the chain rule:

$$\text{I. } \partial f\_H/\partial x = b, \quad \partial f\_H/\partial y = \delta(1+\sigma), \quad \partial f\_H/\partial z = -\gamma$$

$$\text{II. } \partial f\_G/\partial x = \lambda, \quad \partial f\_G/\partial y = 0, \quad \partial f\_G/\partial z = \mu$$

$$\text{III. } \partial f\_M/\partial x = -\theta, \quad \partial f\_M/\partial y = -\nu, \quad \partial f\_M/\partial z = 0$$

Plugging in and writing the Jacobian as a block matrix with $x^*(1-x^*)$ and $z^*(1-z^*)$ factored out where relevant:

Jacobian matrix

$$J(x^*, 0, z^*) = \begin{vmatrix} x^*(1-x^*)\cdot b & x^*(1-x^*)\cdot\delta(1+\sigma) & -x^*(1-x^*)\cdot\gamma \\ 0 & f\_G(x^*, 0, z^*) & 0 \\ -z^*(1-z^*)\cdot\theta & -z^*(1-z^*)\cdot\nu & 0 \end{vmatrix}$$

Source: Author's own calculations

where $f\_G(x^*, 0, z^*) = (c\_P - c\_E - \lambda) + \lambda \cdot x^* + \mu \cdot z^* = c\_P + \mu \cdot z^* - c\_E - \lambda(1 - x^*)$.

Step 3. Block structure and eigenvalues.

Because row 2 has zeros in columns 1 and 3, the Jacobian has a block-triangular structure. The eigenvalue associated with the y-direction is therefore simply the (2,2) entry:

The eigenvalue associated with the y-direction is therefore simply the (2,2) entry:

$$\lambda_\gamma = f\_G(x^*, 0, z^*) = c\_P + \mu \cdot z^* - [c\_E + \lambda(1 - x^*)] \qquad (8)$$

Equation (8) is the central stability result for the state. The eigenvalue is negative meaning small perturbations toward enforcement die out and the state remains at the persuasion corner of

$$c\_P + \mu \cdot z^* < c\_E + \lambda(1 - x^*) \quad \text{(Condition S)}$$

In words: persuasion remains optimal for the state when the total cost of persuasion (its direct cost c_P plus the misinformation-induced erosion $\mu \cdot z^*$) is less than the total cost of enforcement (its direct cost c_E plus the political cost of visible coercion $\lambda \cdot (1 - x^*)$, which scales with the size of the refusing population that would have to be coerced). The 2025 Punjab campaign's observation $y = 0$ implies that Condition S held at the time of the campaign.

Step 4. Eigenvalues of the (x, z) sub-block.

Stripping out row 2 and column 2 leaves the 2×2 sub-Jacobian

$$J_2 = \begin{vmatrix} x^*(1-x^*) \cdot b & -x^*(1-x^*) \cdot \gamma \\ -z^*(1-z^*) \cdot \theta & 0 \end{vmatrix}$$

which governs the dynamics of x and z when y is held at zero. The trace and determinant of J_2 are

$$tr(J_2) = x^*(1-x^*) \cdot b > 0 \qquad (9)$$

$$\det = -(x^*(1-x^*)\gamma)(z^*(1-z^*)\theta) < 0.$$

$$\det(J_2) = 0 - (-x^*(1-x^*) \cdot \gamma)(-z^*(1-z^*) \cdot \theta) = -x^*(1-x^*) \cdot z^*(1-z^*) \cdot \gamma \cdot \theta < 0 \qquad (10)$$

Since $\det(J_2) < 0$, the two eigenvalues of J_2 are real and of opposite sign. Geometrically, the interior point (x^*, z^*) is a saddle in the (x, z) plane. One direction is locally attracting (the stable manifold) and the other is locally repelling (the unstable manifold).

The Jacobian matrix shows that the observed 2025 equilibrium is fragile because the system sits near a saddle, and small parameter shocks such as a misinformation surge raising effective γ, a decline in perceived disease risk lowering b, and a change in the social-influence return θ from a new political actor, can push the system toward one of two corners. The location of the campaign on the stable manifold determines which corner is approached. The absence of a stable interior equilibrium means that maintaining 81 percent coverage requires continued active management, and not a passive expectation that the system will remain at the current equilibrium.

Proposition 1. Consider the replicator system (4) under the linear-risk specification $\rho(x) = x$ and with parameters as defined in Table 5. The point $(x^*, 0, z^*)$ defined by

$$x^* = 1 - (c_A + w_M)/\theta, \quad y^* = 0, \quad z^* = [b \cdot x^* - (c_v + w)] / \gamma$$

is a rest point of (4) whenever the following parameter conditions hold:

(i) $0 < c_A + w_M < \theta$ [x^* is interior]

(ii) $c_v + w < b \cdot x^* < c_v + w + \gamma$ [z^* is interior]

(iii) $c_P + \mu \cdot z^* < c_E + \lambda(1 - x^*)$ [Condition S; $y = 0$ is locally stable]

Under (i)–(iii), the y-direction eigenvalue of the Jacobian at $(x^*, 0, z^*)$ is strictly negative, while the (x, z) sub-Jacobian has trace $x^*(1-x^*) \cdot b > 0$ and determinant $-x^*(1-x^*) \cdot z^*(1-z^*) \cdot \gamma \cdot \theta < 0$. The interior point (x^*, z^*) is therefore a saddle in the (x, z) plane, and the full equilibrium $(x^*, 0, z^*)$ is locally unstable along the unstable manifold of this saddle, even as it is locally stable along the y-direction and along the stable manifold of the (x, z) saddle.

Proof. Equations (6) and (7) make $f_H = 0$ and $f_M = 0$ at the point; together with $y = 0$ they imply $F_1 = F_2 = F_3 = 0$, establishing that $(x^*, 0, z^*)$ is a rest point. Conditions (i) and (ii) ensure $x^*, z^* \in (0,1)$. The Jacobian computation in Section 5.4 yields the stated trace and determinant of J_2 and the y-eigenvalue (8). Condition (iii) is equivalent to (8) being negative. The signs of trace and determinant of J_2 imply real eigenvalues of opposite sign by the standard quadratic-formula calculation.

Proposition 1 yields several testable comparative statics that motivate the scenario analysis of Section 6. Differentiating (6) and (7) with respect to the parameters:

$\partial x^*/\partial\theta = (c_A + w_M)/\theta^2 > 0$ [reducing misinformation's influence return lowers x^*; raising deterrence raises x^*]

$\partial x^*/\partial c_A = -1/\theta < 0$ [making misinformation cheaper to produce lowers acceptance]

$\partial z^*/\partial b = x^*/\gamma > 0$ [a stronger perceived benefit raises the equilibrium misinfo prevalence, holding x^*]

$\partial z^*/\partial\gamma = -[b\cdot x^* - (c\_v+w)]/\gamma^2 < 0$ [higher misinformation sensitivity lowers equilibrium z*; the system relies on less active misinfo to hold the same x*]

Reducing the social-influence return to misinformation (θ) lowers x* in equation (6); but this is because, with θ lower, the misinformation actor exits the market at lower coverage levels, so x* settles at a value where the actor is just indifferent at a lower x*. This means that simply suppressing the misinformation "return" (e.g., through platform moderation) without complementary household-side interventions can lower acceptance, because the equilibrium depends on the misinformation actor's indifference condition.

Second, equation (8) implies that the state's choice to deploy enforcement ($y > 0$) becomes attractive only when $c\_E + \lambda(1 - x^*)$ falls below $c\_P + \mu\cdot z^*$. This can be achieved either by lowering enforcement costs (e.g., by tying vaccination to existing administrative touchpoints such as BISP enrolment, school registration, or NIC issuance, which lowers c_E) or by raising the political cost of inaction (λ falls because the public expects coercion when refusal pockets are visible).

Under the present specification, mechanically raising y from 0 to 0.3 lowers x* from 0.71 to 0.62. The misinformation actor's indifference condition (equation 6, extended for $y > 0$) yields $x^* = 1 - (c\_A + w\_M + \nu y)/\theta$, which is decreasing in y because $\nu\cdot y$ enters the misinformation actor's cost. Equivalently, enforcement deters some misinformation activity (the $\nu\cdot y$ term), but with x* tied to the actor's indifference condition, the equilibrium acceptance rate falls. The model predicts that naive enforcement, without complementary household-side or misinformation-side interventions, can reduce the equilibrium acceptance rate even as it raises mechanical vaccination through compliance.

5.5 Discussion: Linearity, Heterogeneity, and Extensions

The linear specification $\rho(x) = x$ is standard but understates the herd-immunity nonlinearity that becomes important at high coverage. A more realistic specification would be concave: $\rho(x) = x^\kappa$ with $\kappa \in (0, 1)$, or a logistic form. The qualitative results of Proposition 1 carry over to any monotone concave $\rho(\cdot)$, although the algebraic expressions for z* in equation (7) become implicit rather than closed-form. Because Punjab's 2025 coverage of 81 percent is below the herd-immunity threshold (which for HPV with single-dose efficacy is approximately 80–85 percent of the female adolescent cohort), the linear approximation is adequate for the present analysis.

Second, the model treats households as a single population. In reality, the geographic heterogeneity with southern Punjab and urban Lahore exhibiting distinct refusal patterns suggests that the parameters (γ in particular, the responsiveness to misinformation) may vary across districts. A multi-type extension would replace x with a vector $(x_1, \ldots, x_n)$ of district-level acceptance rates, each with its own parameter vector. We treat this as a direction for future work; the present model captures the average behaviour to which the comparative statics apply.

Third, the time scale at which replicator dynamics operate — typically interpreted as adaptive learning over many social interactions — is faster than the actual campaign window of three weeks. Strictly, what we have characterised as an equilibrium is more accurately a quasi-equilibrium achieved within the campaign's operational time.

6. PARAMETARISATION AND SIMULATION

6.1 Parameterization Strategy

The model has thirteen parameters (Table 1). Three are normalisations ($b = 1$, $\theta = 1$, $\alpha = 1$) and one composite ($c_A + w_M$) is identified jointly rather than separately, leaving nine free parameters to be fixed by the available anchors. We use the following hierarchy of constraints, in descending order of empirical strength.

First, we use the misinformation actor's indifference condition (equation 6) to pin down $c_A + w_M$. The observed acceptance rate among contacted households in 2025 was x_{obs} = 6,748,717 / 9,488,457 = 0.7113, where the denominator is the sum of vaccinations and recorded refusals. Setting $x^* = 0.71$ in equation (6) implies

$$c_A + w_M = \theta \cdot (1 - x^*) = 1.00 \cdot (1 - 0.71) = 0.29 \qquad (11)$$

Second, we use the household indifference condition (equation 7) to relate γ, $c_v + w$, and z^*. We do not observe z^* directly, but a plausible range for the share of misinformation actors actively engaged during the September 2025 campaign is 0.3–0.5, given the documented activity of TikTok and Facebook influencers and the emergence of religious opposition in the campaign's second week. γ captures household responsiveness to misinformation (Jarrett et al. 2015). Because γ is not directly observable, it is calibrated to reproduce the observed acceptance rate and subsequently evaluated through sensitivity analysis. We adopt $z^* = 0.42$ as a central value. Together with $c_v + w = 0.50$, justified below, equation (7) implies

$$\gamma = [b \cdot x^* - (c_v + w)] / z^* = (0.71 - 0.50)/0.42 = 0.50 \qquad (12)$$

Following the Vaccine Confidence Index framework by Larson et al. (2015), perceived vaccination costs and refusal incentives are represented through a composite behavioural parameter (Botwright et al., 2017). Given moderate confidence levels observed in Pakistan and other LMIC settings, we calibrate the composite parameter at an intermediate value $c_v + w = 0.50$, consistent with a moderate-trust environment rather than a high- or low-confidence extreme (Galbiati & Vertova, 2014; Galbiati, Henry & Jacquemet, 2018).

Fourth, we parameterize the state-side parameters (c_P, c_E, λ, μ) to satisfy Condition S (eq. 8) at the baseline. The observed campaign overhead of Rs. 5.88 million against vaccinations valued at the Gavi co-financing price of approximately Rs. 154 (USD 0.55 × 280) per dose implies a persuasion overhead share of approximately 0.57 percent of programme value. This figure is a lower bound on the true cost of persuasion, because the recorded overhead line captures incremental administrative expenditure only and excludes the opportunity cost of lady health worker contact time, mobilisation and media effort, and pre-launch religious-leader engagement, none of which are separately costed in the campaign accounts; comparable delivery-cost studies find that such personnel and mobilisation components dominate the total cost of HPV delivery (Botwright et al., 2017). We set $c_P = 0.05$. For c_E, (Gentzkow&Kamenica,2014) report that enforcement-linked delivery in mandate settings costs approximately six times more per dose than persuasion-only delivery; accordingly we set $c_E = 6 \times c_P = 0.30$. The political cost of visible coercion (λ) and the misinformation drag on persuasion (μ) are set at 0.40 and 0.20 respectively, values that satisfy Condition S at the baseline (LHS = 0.13 < RHS = 0.42, comfortably in the persuasion region). Note that the seven state-side parameters (c_P, c_E, λ, μ, δ, σ, ν) do not affect the baseline equilibrium values of x^* and z^* because $y^* = 0$ at baseline; they enter only in the scenario simulations of Section 6.3.

Fifth, the remaining parameters (δ, σ, ν) governing enforcement effectiveness are set at mid-range values (0.50, 0.50, 0.30). These parameters do not affect the baseline equilibrium because $y = 0$; they become operative only in counterfactual scenarios with $y > 0$.

Table 6a. Parameterized parameter values

Symbol	Value	Parameterization anchor / source
b	1.00	Normalisation (benefit unit)
θ	1.00	Normalisation (influence-return unit)
$c_A + w_M$	0.29	From $x^* = 0.71$ via eq. (6): $c_A + w_M = \theta(1 - x^*)$
$c_v + w$	0.50	Following Larson et al. (2018) we adopt an intermediate calibration value (0.50) for the composite household parameter to represent a moderate-trust environment and examine its robustness through sensitivity analysis.

γ	0.50	Implied from $z^* = 0.42$, eq. (7): $\gamma = (b \cdot x^* - c\_v - w)/z^*$
c_P	0.05	Punjab campaign overhead Rs. 5.88M, normalised to benefit scale
c_E	0.30	Estimated 6× persuasion based on Indian mandate enforcement costs
λ	0.40	Political cost of coercive gap; chosen so Condition S holds at baseline
μ	0.20	Misinformation erosion of persuasion; moderate range
δ	0.50	Compliance gain under enforcement; mid-range assumption
σ	0.50	Detection probability under typical conditional enforcement
ν	0.30	Enforcement deterrence on misinformation activity

Source: Author's own calculations

Because several parameters, particularly $z^* = 0.42$ (and therefore $\gamma = 0.50$) and $c\_v + w = 0.50$ are assumptions rather than independently estimated quantities, Table 6a reports how the equilibrium values

x^* and z^* respond to ±20 percent variation in each of the five parameters that enter equations (6) and (7). Parameters are varied one at a time holding all others at baseline.

Table 6b: Sensitivity analysis

Parameter	Baseline	−20% value	x^* at −20%	z^* at −20%	+20% value	x^* at +20%	z^* at +20%
θ	1.00	0.80	0.638	0.275	1.20	0.758	0.517
c_A + w_M	0.29	0.232	0.768	0.536	0.348	0.652	0.304
γ	0.50	0.40	0.710	0.525	0.60	0.710	0.350
c_v + w	0.50	0.40	0.710	0.620	0.60	0.710	0.220
b	1.00	0.80	0.710	0.136	1.20	0.710	0.704

Source: Author's own calculations

Sensitivity analysis shows that x^* responds only to θ and (c_A + w_M), and is insensitive to b, γ, and c_v + w. These findings imply that x^* depends only on misinformation-actor parameters, such that household-side parameters can only shift z^*. Scenario results that depend on changes to x^* (Scenarios B, C, D) are robust to household-side parameter uncertainty; those that depend on z^* (the fragility argument and Scenario F) are more sensitive.

6.2 Baseline Equilibrium and Internal Consistency Checks

At the parameterized parameter values of Table 6a, the interior equilibrium identified in Proposition 1 takes the values

$$x^* = 0.710, \quad y^* = 0.000, \quad z^* = 0.420$$

by construction. Three internal-consistency checks confirm that this configuration is mathematically and substantively coherent.

Check 1. Condition S holds.

Substituting $x^* = 0.71$ and $z^* = 0.42$ into Condition S:

$$\text{LHS} = c\_P + \mu \cdot z^* = 0.05 + 0.20 \cdot 0.42 = 0.134$$

$$\text{RHS} = c\_E + \lambda \cdot (1 - x^*) = 0.30 + 0.40 \cdot 0.29 = 0.416$$

With LHS < RHS by a margin of 0.282, the persuasion-only corner is robustly stable in the y-direction. Equivalently, the state's choice to allocate zero expenditure to enforcement is rationalised by parameters lying well inside the persuasion region; only a substantial increase in the misinformation drag (μ) or a substantial fall in enforcement costs (c_E) would shift the state toward enforcement under the present parameterization.

Check 2. The y-direction Jacobian eigenvalue is negative.

From equation (8), $\lambda\_y = \text{LHS} - \text{RHS} = 0.134 - 0.416 = -0.282$. Negative as required for local stability of $y = 0$.

Check 3. The (x, z) sub-Jacobian has the saddle signature.

Computing trace and determinant of J_2 at (x^*, z^*):

$$\text{tr}(J_2) = x^*(1-x^*) \cdot b = 0.71 \cdot 0.29 \cdot 1.00 = 0.206 > 0$$

$$\det(J_2) = -x^*(1-x^*) \cdot z^*(1-z^*) \cdot \gamma \cdot \theta = -0.71 \cdot 0.29 \cdot 0.42 \cdot 0.58 \cdot 0.50 \cdot 1.00 = -0.0251 < 0$$

The eigenvalues of J_2 are therefore real with opposite signs: $\lambda_1 = +0.292$ (unstable manifold) and $\lambda_2 = -0.086$ (stable manifold). The interior point is a saddle in the (x, z) plane, confirming the analytic result of Section 5.4.

Figure 2 is the phase portrait of the (x, z) system for $y = 0$. The interior point (0.71, 0.42) is the intersection of the two response curves $f\_H = 0$ and $f\_M = 0$, and is indicated with a red star. The saddle structure is illustrated through sample trajectories starting from a variety of initial conditions: trajectories that start a little above the stable manifold end up at the refusal corner (0, 1), whereas trajectories that start a little below the stable manifold end up at the pro-vaccine corner (1, 0).

Figure 2. Phase portrait of the (x, z) replicator dynamics at $y = 0$, baseline parameterization. Arrows show the direction field; sample trajectories (black) illustrate convergence behaviour. The interior saddle is at $(x^*, z^*) = (0.71, 0.42)$.

Source: Author's own calculations

6.3 Scenario Simulations

We simulate four counterfactual policy scenarios. These are not predictions in the forecasting sense; they are comparative statics exercises that ask what equilibrium the model implies under a hypothesised parameter change, holding the rest of the parameterization fixed. In each scenario, the state commits to a policy variable y and possibly to other parameter changes; the household and misinformation populations then adjust to the new (x, z) equilibrium dictated by their indifference conditions. This commitment interpretation is appropriate for a planned campaign of finite duration, in which the state does not have time to re-optimise within the campaign window. We emphasise that the validity of any scenario result depends entirely on the validity of the underlying parameter change being a reasonable representation of the intervention — an assumption that has not been tested against out-of-sample data.

The scenarios are: (A) the 2025 baseline as observed; (B) naive enforcement, in which the state moves to $y = 0.30$ with no other change; (C) religious-leader pre-engagement, in which the state lowers the misinformation actor's social-influence return from $\theta = 1.00$ to $\theta = 0.80$ with y held at zero; (D) a combined intervention pairing pre-engagement ($\theta = 0.80$) with modest enforcement ($y = 0.10$). Table 7 reports the resulting equilibrium values of x* and z*.

Table 7. Acceptance-rate equilibria across scenarios

Scenario	y	θ	x*	z*
A. Baseline (2025 observed)	0.00	1.00	**0.710**	0.420
B. Naive enforcement	0.30	1.00	**0.620**	0.690
C. Religious leader pre-engagement	0.00	0.80	**0.637**	0.275
D. Combined	0.10	0.80	**0.600**	0.350

Source: Author's own calculations

The following are the main findings of the model:

I. Naive enforcement (Scenario B) lowers acceptance from 0.71 to 0.62. This is the counter-intuitive result previewed in Section 5. Mechanically, the misinformation actor's indifference condition (extended for $y > 0$) gives $x^* = 1 - (c\_A + w\_M + \nu y)/\theta = 1 - (0.29 + 0.30 \cdot 0.30)/1.00 = 0.62$. The enforcement deterrent on misinformation (νy) shifts the equilibrium acceptance rate downward, not upward. Equivalently: enforcement pushes some misinformation actors to exit the market, but the equilibrium acceptance rate that sustains misinformation indifference is now lower.

II. Religious-leader pre-engagement alone (Scenario C) lowers acceptance, from 0.71 to 0.64. The mechanism is similar but operates through θ rather than ν: a lower influence return raises the relative attractiveness of the misinformation actor's silence option, and the indifference point moves to a lower x^*. This finding could be surprising in the public-health policy discourse, in which religious-leader engagement is rarely characterized as a one-way street. In this specification, acceptance and misinformation are co-determined, with the result that the acceptance rate in equilibrium is lower with pre-engagement, while the prevalence of misinformation drops lower (from 0.42 to 0.28).

III. The combined intervention (Scenario D) does not rescue the result: x^* falls further to 0.60. The reason is that both interventions push the indifference equilibrium in the same direction; combining them compounds the acceptance decline rather than offsetting it.

Figure 3 shows the three intervention scenarios as time-series. For every one of the panels, the trajectories starting from a common initial condition ($x_0 = 0.65$, $z_0 = 0.45$) tend to the equilibrium value as given in Table 7. This divergence is a numerical check of the simulation code to make sure that it implements the closed form equilibrium that was derived analytically in Section 5 but is not a test of the correctness of the equilibrium values themselves, since both are derived from the same parameterized parameters.

Figure 3. Time-series trajectories under Scenarios A, B, and D. Each panel shows the divergence of acceptance (x, blue solid) and misinformation prevalence (z, red dashed) toward the equilibrium values reported in Table 8. Dotted horizontal lines mark these equilibrium values.

Source: Author's own calculations

6.4 The Coverage Decomposition: Acceptance Is Not Coverage

The results in Table 8 indicate that each policy intervention reduces the equilibrium acceptance rate, implying that there is no reason to move away from the 2025 status quo, as it is locally optimal. This conclusion is flawed because it confuses two different terms: acceptance rate amongst contacted households and total population coverage. The high coverage for the 2025 campaign was not due to a high level of x* alone, but also to a high level of κ; the high level of κ for this campaign was achieved by dividing the coverage rate, 6,878,311/8,536,154 = 0.806, by the acceptance rate among contacted households, 0.711, so that the contact intensity index κ = 0.806/0.711 = 1.13. The value for the ratio κ > 1 does not necessarily mean that more girls were vaccinated than the number of girls in the eligible population; it could be the result of some households being contacted multiple times via school and community pathways, and variation in the number of girls in the denominators between the school and community pathways as a result of pathway revisitation protocols. In this decomposition, κ is best interpreted as a contact intensity index: κ > 1 indicates that the campaign made more than one effective contact per eligible girl on average, a feature of the community channel's 202 percent over-performance against its planned target documented in Table 2.

The model's comparative-static result that demand-side interventions move x* downward follows directly from the parameterized equilibrium condition, not from an independent forecast; it is a feature of how the model is constructed, conditional on the assumed z*. That said, it points to a policy-actionable insight: contact intensity κ is the dominant lever for coverage, and contact intensity is not pinned down by the misinformation-actor indifference condition. κ is determined by operational decisions such as number of community vaccinators deployed, density of mobile camps, number of door-to-door visits per refusing household, school engagement rates that the planner controls directly.

Table 8 reports the coverage implications of the scenarios when contact intensity is incorporated. Scenarios A through D all hold κ at the 2025 value of 1.13. Scenarios E and F introduce contact expansion: κ is raised to 1.30, corresponding to a 15 percent expansion of community outreach above the 2025 level, which is operationally feasible given that the 2025 community channel already exceeded its target by 102 percent and could plausibly absorb further surge.

Table 8. Coverage decomposition: scenarios with and without contact expansion

Scenario	**x* (acceptance)**	**Contact rate κ**	**Coverage κ·x* (capped at 1)**	**vs. 2025 (81%)**
A. Baseline (2025)	0.710	1.13	**0.806**	—
B. Naive enforcement	0.620	1.13	**0.70**	−10 pp

C. Pre-engagement only	0.637	1.13	**0.72**	−8 pp
D. Combined (θ↓, y↑)	0.600	1.13	**0.68**	−13 pp
E. Contact expansion (κ↑)	0.710	1.30	**0.92**	+11 pp
F. Combined (θ↓ + κ↑)	0.637	1.30	**0.83**	+2 pp

Source: Author's own calculations

Scenarios B, C, and D which represent the demand-side interventions that lower x* through the indifference channel, reduce coverage by 8–13 percentage points. Scenario E, which leaves x* untouched at the 2025 value and expands contact intensity from 1.13 to 1.30, lifts coverage from 0.806 to 0.924 (approximately 92 percent), crossing the WHO benchmark. Scenario F, which combines pre-engagement (reducing the saddle's instability via lower θ) with contact expansion, achieves 83 percent coverage — a modest improvement over baseline but with the additional benefit of reduced fragility, since lower θ reduces the equilibrium misinformation prevalence.

7. POLICY RECOMMENDATION

7.1 Recommendation 1: Community Outreach

The one lever that has the greatest potential to do more at the next stage is the scaling up of community outreach. In the 2025 Punjab campaign, operational targets were roughly split between school vaccinators (71 percent) and community vaccinators (29 percent), with the actual allocation taking place during the implementation.

The expectation for the performance of a community channel should include multiple visits, not single-pass contact. A large part of the 2025 community channel's 202 percent over-performance against its operational target is due to vaccinators going back to households where the initial visit resulted in a refusal or lack of vaccination. Based on the observed contribution of revisitation to the community channel's overperformance (Section 6.4), explicit scheduling of at least two visits prior to recording a hard refusal appears operationally reasonable, though the paper's administrative data cannot establish how many of the 2025 community contacts were genuine revisits versus first contacts, so the marginal value of a specific revisit count is not something this model can quantify.

Thirdly, mobile camps should be considered for geographically isolated tehsils and union councils on a proactive basis, though this recommendation rests on operational reasoning about the contact-intensity decomposition rather than on a formally modelled prediction of district-level outcomes. Low coverage in southern districts, such as Rajanpur (73 percent), Multan (75 percent), and Khanewal (75 percent), is partly due to the difficulty of accessing girls who live in dispersed communities with standing community-vaccinator programs. In Balochistan, especially where settlement geography is physically more dispersed, mobile camps will be required and should be provided at multiples of the per-girl rate for Punjab.

7.2 Recommendation 2: Pre engage religious authorities

The mechanism that the model suggests could help reduce θ prior to launch is religious-leader pre-engagement. Although pre-engagement reduces the equilibrium acceptance rate in the model, we recommend it as a fragility-reduction strategy because a lower θ shrinks the basin of attraction of the refusal corner. During the 2025 Punjab campaign, religious opposition was not a significant factor until the second week of the campaign, when social media misinformation had already set the tone of the vaccination as a 'foreign funded fertility intervention' (Furqan, Rahim and Haider, 2025). The Council of Islamic Ideology made a clarifying statement, but this came after the framing had set in somewhat. Based on this timing pattern, we suggest that provincial ulema engagement undertaken in advance of the campaign, with Friday sermon coordination and Council of Islamic Ideology endorsement, may be more effective than the reactive approach observed in Punjab's second week. This is a plausible operational inference from the Punjab timeline, not a tested prediction for the other provinces.

7.3 Recommendation 3: Targeted Urban Misinformation Strategy

The pattern in geographic performance is not in line with the conventional rural-urban gradient in health outcomes: Lahore has the highest female literacy ratio in Punjab, yet underperformed at 82 percent. The model implies that the mechanism behind this is a higher γ (greater responsiveness to misinformation) in urban areas due to social-media penetration, with the lower equilibrium acceptance rate in Lahore arising despite more favourable structural conditions.

A relaunch should include 2 elements that are specifically about the urban context:

I. Pre-emptive engagement with the health influencers, religious influencers, and lifestyle influencers who are followed by large numbers of their target audience: TikTok and Facebook for the general audience; YouTube for longer-form religious and political-oriented content; and X (formerly Twitter) for journalist and political-class amplification. It was observed that the Council of Islamic Ideology's post hoc statement, although authoritative, did not change the framing done by the social media influencers in first week, which is a challenge that can only be met if the relaunch happens on the same platforms and in the same time.

II. Second, fast monitoring of reports on anti-vaccine social media activity. A small number of high-reach social media posts appear capable of shifting public sentiment in an urban district within a short window of days. It is important to have cells based on Provincial information who can identify and respond to it during the campaign period, and prepare the response materials in Urdu, Pashto, Sindhi and Balochi.

8. CONCLUSION, LIMITATIONS AND FUTURE RESEARCH DIRECTION

8.1 Conclusion

In Pakistan, the September 2025 HPV vaccination campaign in Punjab had an overall eligible-cohort coverage of 81 percent with low direct campaign overhead and without relying on enforcement, and with a high geographic clustering of household refusals in the south of Punjab and unusually the largest urban district. This paper has described the cost structure of the campaign, the outcomes of the coverage, and the composition of the delivery channels, as well as parameterized a three-player evolutionary game of strategic interaction among a household, a state, and a misinformation actor to the 2025 outcomes and evaluated four canonical scenarios that could be used in the 2026 and 2027 phases.

Three things are crucial in the findings, each carrying a different degree of evidentiary weight. First, the community outreach was greater than the school-based delivery, the exact opposite of what had been recommended in the Rwandan experience—62.7 percent of vaccinations were recorded at the community level, compared to 49 percent in school. This is a directly observed fact from the administrative data, not a model-derived result. Second, under the model's parameterization, an interior equilibrium structured as a saddle exists, in which household acceptance is pinned to the misinformation actor's indifference condition: the model-implied consequence is that the observed acceptability level of 71 percent is difficult to raise using demand-side interventions alone (information campaigns, religious leader engagement, conditional enforcement) without also addressing contact intensity, and that some demand-side interventions can even lower x^* in the model. This finding is a feature of the parameterized model conditional on the assumed z^*, not an independently validated empirical regularity; it should be read as a theoretical implication worth testing, not an established fact about household behaviour. Third, decomposing population coverage into contact intensity and acceptance rate suggests that the dominant lever for the relaunch is supply-side intensification of community outreach rather than demand-side persuasion — a conclusion we consider the paper's best-supported policy implication, since it follows from the observed 2025 contact-rate arithmetic (Section 6.4) rather than from the more assumption-dependent scenario simulations.

8.2 Limitations

This model has several limitations that future researchers can address. First, the parameterization relies on an assumed value of z^*, the share of misinformation actors actively engaged, which is not observed in the administrative data; every scenario result that depends on z^* should be read as illustrative of direction and order of magnitude, not as a tested prediction. Second, the model is parameterized to province-wide Punjab aggregates; district-level patterns discussed in Section 4 and Section 7.3 are offered as illustrations consistent with the model's mechanism, not as out-of-sample validation, since γ and θ are not independently estimated at the district level. Third, the extension of the model's implications to KPK, Balochistan, and Gilgit-Baltistan is a plausibility argument based on the Punjab parameterization; it has not been tested against data from those provinces, which have different demographic, infrastructural, and religious-authority landscapes.

8.3 Future research direction

Future researchers can use actual micro level data to conduct empirical analysis. Future research using household-level survey data, school-level administrative records, and district-level misinformation exposure measures would allow z^*, γ, and θ to be independently estimated rather than parameterized, which would convert several of this paper's plausibility arguments into testable predictions.

Data availability statement

The data used in this study were obtained from administrative records of the Punjab Expanded Programme on Immunization (EPI) HPV Vaccination Campaign conducted between 15 September and 4 October 2025. The analysis relies exclusively on aggregated campaign-level and district-level statistics on vaccinations, refusals, coverage rates, delivery channels, and campaign costs. No individual-level records or personally identifiable information were accessed or used. Due to administrative and institutional restrictions governing the dissemination of government health records, the underlying dataset is not publicly available. Researchers interested in accessing similar data should contact the relevant public health authorities in Punjab, Pakistan, subject to applicable permissions and regulations.

Ethics Statement

This study is based on aggregated administrative data collected during routine public health operations. No human participants were directly recruited, surveyed, interviewed, or experimented upon for the purposes of this research. No individual-level health information or personally identifiable information was accessed. As the analysis uses anonymized aggregate statistics, formal ethical review and informed consent requirements were not applicable under standard research ethics guidelines.

Conflict of Interest Statement

The authors declare no conflict of interest related to the preparation, analysis, or publication of this research.

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Appendix

Table A1. HPV Vaccination Coverage (15 Sep – 4 Oct 2025)

	Target, #	**Covered, #**	**Covered, %**
Schools	**127,688**	**-**	**-**
School vaccinations	**5,172,606**	**2,518,752**	**49**
Community vaccinations	**2,094,744**	**4,228,965**	**202**
Total vaccinations	**7,267,350**	**6,748,717**	**93**
Refusals	**2,739,740**		

Source: EPI Campaign MIS

Table A2. District-Wise HPV Coverage, Punjab

District	Target, #	Vaccinated, #	Vaccinated, %
Okara	219,624	200,785	91%
Sheikhupura	254,460	221,865	87%
Jhelum	95,952	83,500	87%
Bhakkar	136,992	117,335	86%
Rahimyar Khan	385,284	327,723	85%
Rawalpindi	395,700	336,907	85%
Pakpattan	139,522	117,818	84%
Faisalabad	595,116	495,791	83%
Kasur	285,672	237,046	83%
Bahawalpur	298,960	247,940	83%

Sahiwal	**182,040**	**150,872**	**83%**
Jhang	**194,664**	**160,983**	**83%**
Chiniot	**99,060**	**81,441**	**82%**
Lahore	**931,860**	**764,811**	**82%**
Sargodha	**302,832**	**248,030**	**82%**
Toba Tek Singh	**174,816**	**142,333**	**81%**
Mianwali	**125,520**	**101,888**	**81%**
Gujranwala	**368,064**	**296,794**	**81%**
Nankana Sahib	**114,756**	**92,299**	**80%**
Sialkot	**284,832**	**223,534**	**79%**
Khushab	**104,820**	**81,204**	**78%**
Hafizabad	**71,524**	**55,139**	**77%**
Layyah	**146,436**	**112,673**	**77%**

Lodhran	**133,968**	**102,892**	**77%**
Vehari	**239,940**	**183,698**	**77%**
D.G Khan	**237,324**	**181,575**	**77%**
Attock	**129,060**	**98,275**	**76%**
Chakwal	**111,156**	**84,397**	**76%**
Muzaffargarh	**328,572**	**248,849**	**76%**
Mandi Bahauddin	**127,272**	**96,184**	**76%**
Narowal	**121,152**	**90,971**	**75%**
Bahawalnagar	**242,088**	**181,405**	**75%**
Multan	**372,204**	**278,875**	**75%**
Khanewal	**234,228**	**174,687**	**75%**
Gujrat	**183,872**	**136,915**	**75%**
Rajanpur	**166,812**	**120,877**	**73%**

Punjab	**8,536,154**	**6,878,311**	**81%**

Table A3. HPV Vaccine Distribution by District

District	September 2025	January 2026
Attock	131,400	4,200
Bahawalnagar	211,500	6,800
Bahawalpur	254,400	8,200
Bhakkar	129,990	3,800
Chakwal	105,200	3,300
Chiniot	94,500	3,100
D.G Khan	201,900	6,500
Faisalabad	537,400	17,200
Gujranwala	362,700	11,400
Gujrat	195,400	6,100

Hafizabad	**79,800**	**2,500**
Jhang	**185,100**	**6,000**
Jhelum	**83,500**	**2,700**
Kasur	**248,400**	**7,800**
Khanewal	**199,300**	**6,400**
Khushab	**91,200**	**2,900**
Lahore	**792,500**	**23,270**
Layyah	**124,600**	**4,000**
Lodhran	**116,500**	**3,700**
M.B Din	**110,700**	**3,500**
Mianwali	**109,100**	**3,500**
Multan	**316,600**	**10,200**
Muzaffargarh	**297,300**	**9,500**

Nankana Sahib	**97,600**	**3,200**
Narowal	**115,400**	**3,700**
Okara	**208,300**	**6,700**
Pakpattan	**126,900**	**4,100**
Rahimyar Khan	**337,200**	**10,600**
Rajanpur	**141,900**	**4,600**
Rawalpindi	**374,200**	**11,700**
Sahiwal	**174,400**	**5,500**
Sargodha	**257,500**	**8,300**
Sheikhupura	**245,800**	**7,700**
Sialkot	**266,600**	**8,600**
T.T Singh	**152,000**	**4,800**
Vehari	**208,600**	**6,600**

Total	**7,685,390**	**242,670**