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# Adoption of New Technology Vaccines

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**Abstract**

Extensive research has examined the diffusion of innovations for products that can be trialed, and where the most adverse outcome, if a product fails, is a financial loss. However, less research has explored consumer responses to innovations in highly uncertain contexts characterized by health losses, lack of trialability, and the opportunity to free-ride on other's adoption. This research focuses on vaccine decision-making as a unique case within such contexts and extends the findings to other domains. Four studies ($N_{total}$ = 1,796, five supplementary studies, $N_{total}$ = 643) test the propositions of a formal model that incorporates uncertainty and other's choices into the adoption decision. The results show that consumers are surprisingly averse to products that are described as employing a new technology (e.g., mRNA technology) and require an 'efficacy premium' to compensate for higher perceived uncertainty. However, considerable heterogeneity exists due to individual differences in technology readiness, trust in government, and risk attitudes. Notably, despite the prominent threat of free-riding, a social proof nudge (communicating increasing population adoption) effectively reduces aversion to new technology. In this context, social proof information does not merely drive conformity or social learning, but instead increases adoption of new technology by alleviating perceived uncertainty.

*Keywords:* Innovation, Adoption, Uncertainty, Technology Readiness, Social Proof, Pharmaceuticals, Vaccine, Free-riding

When companies introduce new technologies to the market, consumers are expected to adopt the innovation at different time points in a predictable pattern, with distinct consumers categorized as innovators, early adopters, early majority, late majority, and laggards (Rogers 1995). The expectation is that innovators and early adopters perceive a relative advantage in new technologies over older ones and adopt the innovation first. This leads to broader diffusion through a dynamic, cascading process where imitators follow innovators due to increased awareness and word-of-mouth (Bass 1969). However, when a new technology carries the uncertainty of an irreversible health loss, the stakes and complexities are particularly high, presenting unique challenges for consumers and, consequently, managers promoting these products. Traditional adoption models often assume that consumers have the opportunity to trial a new technology, reducing uncertainty through firsthand experience (e.g., in Rogers' (1995) Diffusion of Innovations theory trialability is positively related to the adoption rate). However, sometimes trial opportunities are limited or lacking. Additionally, while the positive influence of other consumers' uptake on technology adoption is well-documented (e.g., Sun 2013), there are contexts in which the adoption of a product by others can paradoxically undermine its importance and lead to free-riding (Hardin 1968; Ostrom et al. 1999). Further, individual differences and underlying beliefs may create heterogeneous barriers to adoption, regardless of the efficacy of new technology.

Despite a rich literature on diffusion of innovations (e.g., Goldenberg et al. 2009; Mahajan, Muller, and Bass 1990; Watts and Dodds 2007), even in the domain of pharmaceuticals (e.g., Desiraju, Nair, and Chintagunta 2004), there remains a significant gap in our understanding of innovations where adoption by some consumers hinders rather than facilitates adoption. We investigate this knowledge gap in the pharmaceutical context. We study vaccine decision-making as a test case of environments where marketing of a new technology introduces complexities that

extend beyond traditional considerations. These complexities include (1) the uncertainty of an irreversible, potentially unobservable health loss, (2) a lack of trialability to alleviate uncertainty, (3) a prominent threat of free-riding, where knowledge of others' adoption decreases willingness to embrace the uncertainty associated with new technology. Similar characteristics exist for innovative pharmaceuticals for transmissible conditions (Kumar et al. 2021) and innovations with externalities, such as nano-technology pesticides (Kahan et al. 2009; Wang et al. 2022; Zhang, Chintagunta, and Kalwani 2021) and alternative energy (Scovell 2022). For instance, hydrogen heating systems are often perceived as more dangerous due to a risk of explosion (i.e., uncertainty of health loss). Once installed, it is difficult to return (i.e., low trialability), and if others' adoption is high, carbon emissions will be lower (i.e., free-riding is attractive).

Technological innovations possessing these characteristics may follow different adoption rules than those devoid of such attributes, and framing a product as innovative may impede rather than accelerate adoption. Hence, marketers may have to adapt their marketing communication. Yet, our understanding of the adoption rules in these contexts has remained limited from a theoretical and practical perspective. Our manuscript addresses this in the following way.

We first develop a mathematical model to study preferences between new and traditional technology in the vaccine context. We study how risk aversion and the tendency to overweight small probabilities (Tversky and Kahneman 1992) influence preferences between new and traditional technology vaccines based on vaccine efficacy and perceived uncertainty of side effects. We then test the model propositions in four experiments. We first quantify the relationship between uncertainty of new technology and the corresponding benefit that consumers require to compensate with an 'efficacy premium'. We then demonstrate a causal relationship where new technology is perceived as more uncertain and therefore requires a larger efficacy premium. Additionally, we

study the effect of a social proof nudge (Cialdini 2001). Consistent with prior research (Agranov, Elliott, and Ortoleva 2021; Hershey et al. 1994), a social proof nudge reduces perceived uncertainty more for new than traditional technology vaccines. However, it does not lead to substantial free-riding which is a prominent concern in this domain (Galizzi et al. 2022). Instead, we argue that social proof acts as a proxy trial experience, reducing uncertainty by providing reassurance, rather than solely promoting conformity or social learning as demonstrated previously (Campbell and Fairey 1989; Cialdini and Goldstein 2004; Deutsch and Gerard 1955; Goldstein, Cialdini, and Griskevicius 2008). Finally, we identify sources of heterogeneity in efficacy premia and responses to social proof, specifically, technology readiness (TR; Parasuraman and Colby 2015), trust in government, and risk attitudes.

Theoretically, we contribute to Rogers' (1995) diffusion of innovations theory by shedding light on adoption rules in high-uncertainty health loss contexts with limited trialability and free-riding. We highlight the causal mechanisms when social proof nudges and individual differences interact with uncertainty perceptions. This conceptualization differentiates our research from existing research on innovations (e.g., enhancement pharmaceuticals (Riis, Simmons, and Goodwin 2008), “really new products” (Feurer et al. 2021) or “big innovations” (Moreau and Wood 2019)), and more generally, from products where herding behavior typically leads to increased adoption (Bikhchandani, Hirshleifer and Welch 1992).

Practically, managers involved in marketing new technologies can use our results to gain insights into the heterogeneity of consumers’ responses and underlying sources of variation in efficacy premia. By identifying these factors, marketers can anticipate multiple consumer segments with different responses and tailor their communication strategies accordingly. For consumers, being aware of how their personal beliefs and attitudes (TR, trust in government, risk

attitudes) affect their technology preferences, could allow them to make more informed choices. In addition, a better understanding of how marketers and policy-maker use social proof nudges, can contribute to improving consumers' decisions.

The remainder of this manuscript is structured as follows. Based on existing literature, we develop a mathematical model and derive predictions for the adoption of new technology vaccines. We then present four empirical studies (supplemented by five studies in the web appendix) which test the model propositions. Finally, we discuss the theoretical and practical implications.

## Theoretical Development

Consider a consumer in health state $h$ and a disease that leads to health loss of $l \leq h$. Each consumer has a subjective probability of infection $p$. To protect against the disease, the consumer can get a vaccine with efficacy $E$ which lowers the probability of health loss $l$ to $p(1-E)$.[1] However, the consumer could experience a side effect $c$ with average subjective probability $q$ when vaccinating. We assume $pl \geq qc$ (i.e., the expected health loss due to infection is higher than due to side effects). We assume a strictly increasing and concave utility function $u$ that transforms the health loss to a subjective value. Although the (average) side effect of a vaccine is $c$, the side effect can either be mild or severe. The subjective probability of mild side effects is $(1-\beta)q$. The subjective probability of severe side effects is $\beta q$. We assume mild side effects are more common than severe side effects, that is $0 < \beta < .5$. We use $\delta > 0$ to represent the perceived uncertainty of side effects. The uncertainty parameter $\delta$ controls the variance of side effects. A mild side effect

[1] We follow the health economics approach modeling vaccine effectiveness by lowering the probability of infection after vaccination (Courbage and Peter 2021; Crainich, Eeckhoudt, and Menegatti 2019). Vaccinating might also lower the disease severity. Results do not change when we incorporate this.

is represented by $c - \frac{\delta}{(1-\beta)q}$ and a severe side effect is represented by $c + \frac{\delta}{\beta q}$, so that the average side effect is $c$. The higher the spread $\delta$, the higher is the variance and therefore, the higher is the uncertainty of side effects.[2] A consumer's decision tree is shown in Figure 1. Note that this illustration does not encompass all possible disease-side effect relationships.

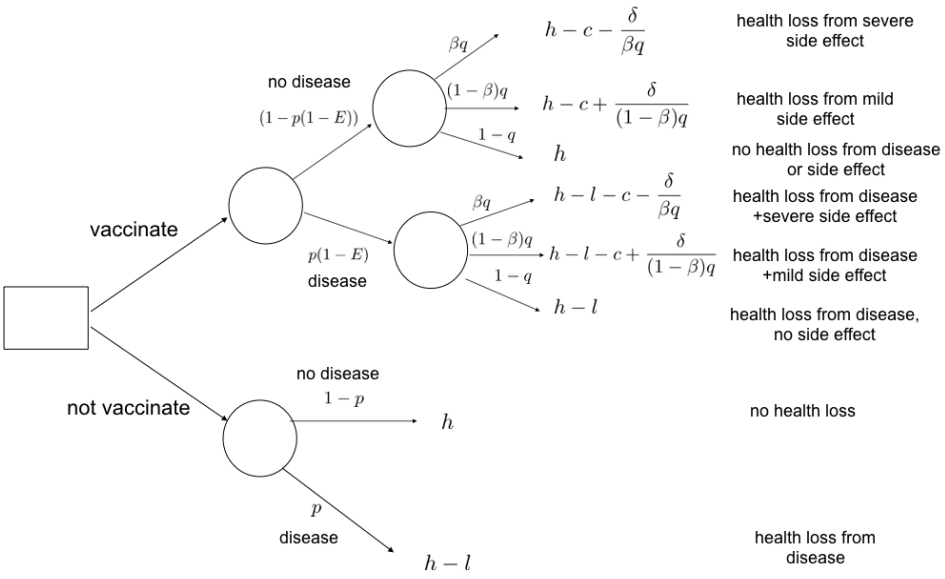


**Figure 1**. Decision tree capturing health outcomes.

As shown in the decision tree, every vaccination decision requires trading off risks (e.g., side effects) and benefits (e.g., not getting severely ill). The factors leading to vaccine hesitancy have been studied extensively (e.g., Dodd et al. 2021; Savoia et al. 2021). For an overview see the Societal Experts Action Network (2023) archive which catalogues over 1,750 pandemic related surveys across 37 countries since 2020. Nevertheless, we argue that a key factor has received little research attention, namely the technology which a vaccine employs.

***New Versus Traditional Technology Vaccines***

[2] As $\delta$ is higher, the variance of side effects ($\sigma^2$) is higher. Since the average side effect is $c$, higher variance implies a higher coefficient of variation ($\sigma/\mu$) which captures uncertainty in a statistical sense.

Some newly developed vaccines use an innovative messenger ribonucleic acid (mRNA) technology. Approval by the U.S. Food and Drug Administration was received in under one year while under normal circumstances it can take up to 15 years (CDC 2023). Compared to routine vaccines that have been tested and used over decades on a large number of people, the potential side effects of mRNA vaccines are considerably more uncertain (e.g., Dag Berild et al. 2022; Fraiman et al. 2022; Sun, Jaffe, and Levi 2022). Survey research indicates that reasons for distrust in COVID-19 vaccines revolved around their novelty and fast-tracked distribution, concerns about inadequate testing and lack of long-term data on side effects (Latkin et al. 2021).

We model the vaccine technology as follows. We consider two vaccines: (i) new technology vaccine and (ii) traditional technology vaccine. We assume the efficacy of the new technology ($E_N$) is at least as high as of the traditional technology vaccine ($E_T$) i.e., $E_N \geq E_T$ (there is some benefit of adopting the new technology). We assume that a consumer perceives the new technology to be more uncertain (i.e., larger $\delta$ or more variance in side effects) than the traditional technology vaccine. We indicate $\delta$ for the new technology by $\delta_N$ and for the traditional technology by $\delta_T$, with $\delta_N > \delta_T$. The side effects of the new technology vaccine are a mean preserving spread of the side effects of the traditional technology vaccine. Statistically, a mean-preserving spread involves one variable having a greater spread or variability in its probability distribution compared to another variable, while both maintain the same mean. In our context, both vaccines have the same average side effects, but the new technology vaccine has higher variance in side effects. Therefore, it is more uncertain (Rothshild and Stiglitz 1970).

Uncertainty is a major deterrent in the adoption of new technology (Mani and Chouk 2018) as it is inversely related to the willingness to try a new product (Bearden and Shimp 1982). As Ram and Sheth (1989, p.8) note "all innovations, to some extent, represent uncertainty and pose

potential side effects that cannot be anticipated." For medical innovations, uncertainty is particularly high because negative consequences of adopting a treatment could be consequential and irreversible for one's health, and further, they might not be immediately observable (e.g., a major deterrent of COVID-19 vaccinations in females is fear about fertility; Diaz et al. 2022). Our model shows that consumers who perceive higher uncertainty about side effects ($\delta$) of a new technology vaccine, are more averse to vaccinate and require higher efficacy to compensate. But individual traits and beliefs affect how consumers perceive uncertainty, and how open they are to technology in general. We incorporate two factors in our model, trust in government and technology readiness (TR), which are expected to affect the parameters and vaccine preferences.

***Trust in Government***

One factor that can affect $\delta_N - \delta_T$ is trust in government and regulatory processes. Vaccine hesitancy appears to be partially an outcome of a breakdown in trust between sections of the population and the government (Kennedy 2020). Lack of trust in government is among the most common reason to avoid COVID-19 vaccines in the U.S. (Hamel et al. 2020). Similarly, U.K. respondents, who were vaccine-hesitant, had higher mistrust in government (Freeman et al. 2022; Murphy et al. 2021). We expect trust in government to play a stronger role for new technology vaccines. Those with lower trust in government should perceive a higher uncertainty of side effects for new technology vaccines and have a higher difference $\delta_N - \delta_T$ in the model. Thus, they should be more averse to adopt a new technology vaccine.

***Technology Readiness***

We also propose technology readiness (TR) as an important factor affecting preferences for new technology vaccines. The Technology Readiness Index (TRI) 2.0 by Parasuraman and Colby (2015) is a well-established construct encompassing consumers' propensity to adopt and

embrace cutting-edge technology at home and in the workplace that has been validated in a variety of contexts, including health (e.g., Lee et al. 2022). The psychographic measure captures motivators to adopting innovations (optimism and innovative tendencies) and inhibitors (insecurity about negative outcomes and discomfort). TR is an important determinant of technology adoption in travel, fintech, education, gaming, agriculture, emerging markets and health care (for a recent meta-analysis, see Blut and Wang 2020). We propose that high TR individuals are less hesitant to adopt a new technology vaccine, irrespective of the perceived uncertainty of side effects. Even though consumers might perceive high uncertainty, this should not deter those with high TR from adopting a new technology vaccine considering that high TR individuals show less insecurity about negative outcomes. In our model, we allow for individual variation in TR by incorporating an $\epsilon$ term. We assume that $E(\epsilon) = 0$. The level of heterogeneity in the willingness to adopt a new technology vaccine will vary based on TR (in which case $\epsilon$ is higher).

Given the model set-up, we now provide the formal results. We first derive the preferences of a subjective expected utility (EU) consumer (Savage 1954). We then incorporate probability weighting and analyze its effect on preferences (Quiggin 1982; Tversky and Kahneman 1992).

***Preferences of an Expected Utility Consumer***

To calculate the EU, we assume the utility function $u$ is strictly increasing and concave, i.e., $u'(x) > 0, u''(x) < 0$. As the new technology vaccine is perceived as having more uncertain side effects, Lemma 1 follows directly.

***Lemma 1.*** *An EU consumer with a concave utility function u prefers taking up the traditional over the new technology vaccine when the difference between their efficacies is small, i.e., when* $E_N - E_T \leq k$ *and* $k \geq 0$.

*Proof.* All proofs are in the web appendix.

Lemma 1 implies that an EU consumer demands higher efficacy (or efficacy premium $E_N - E_T > k$) of the new technology vaccine to compensate for higher perceived uncertainty of side effects.

***Effect of Probability Weighting***

Another factor that can affect vaccine preference is probability weighting. Clinical trials are essential to quantify vaccine safety. But it is difficult to ascertain all possible side effects during a short trial period, especially when severe side effects are rare. Consumers typically pay more attention to such low probabilities of severe consequences (Kahneman and Tversky 1979; Tversky and Kahneman 1992). We therefore study the effect of probability weighting.

Mathematically, after ordering the outcomes, a strictly increasing probability weighting function $w$ is applied to the probabilities based on the rank dependence rule. It leads to a generalized EU model known as the rank dependent utility (RDU; Quiggin 1982). A similar rank dependence rule for transforming probabilities is used in cumulative prospect theory (Tversky and Kahneman 1992; Wakker 2010). Consistent with empirical observations, we assume that the probability weighting function is inverse-S shaped (Kahneman and Tversky 1979).

***Definition 1.*** *A probability weighting function w is inverse-s shaped if it has the following two properties: (i) regressive if it intersects the diagonal only once and from above; (ii) if it exhibits the Cavex property, meaning it is first concave and then convex.*

If the weighting function exhibits the Cavex property, there is an inflection point $p^*$, where the weighting function shifts from being concave to convex. Two widely used inverse-s parametric specifications are $w(p) = \frac{p^\alpha}{(p^\alpha+(1-p)^\alpha)^{1/\alpha}}$ (Tversky and Kahneman 1992) and $w(p) = e^{-(-\ln(p))^\alpha}$ (Prelec 1998), where $0 \leq \alpha \leq 1$. As $\alpha$ approaches 1, consumers process probabilities linearly. We show in Lemma 2 that the inverse-s weighting function leads to a higher efficacy premium.

***Lemma 2.*** *If p<p*, then a consumer with an inverse-s shaped weighting function*

*(i) prefers taking up the traditional over the new technology vaccine when the difference between their efficacies is small $E_N - E_T \leq k'$, where $k' \geq k$;*

*(ii) has a stronger preference for the traditional over the new technology vaccine for lower $\alpha$ (i.e., when there is more overweighting of small and underweighting of large probabilities).*

Lemma 2 implies that consumers with an inverse-s weighting function demand a higher efficacy premium ($E_N - E_T = k' \geq k$) to adopt the new technology vaccine. The efficacy premium increases as consumers overweight small probabilities and underweight large probabilities more.

***Social Proof Nudge: The Population Vaccination Rate***

Self-experimentation is the most common way to learn about new technology. But, since vaccine decisions are irreversible, one-time choices, consumers might look for external information to resolve uncertainty, that is, what others have done. According to the social proof principle, consumers rely on actions of others as a guide for their own behavior, particularly in uncertain situations (Cialdini 2001). Social proof has been an effective nudge in many domains (e.g., Campbell and Fairey 1989; Cialdini and Goldstein 2004; Deutsch and Gerard 1955; Goldstein, Cialdini, and Griskevicius 2008; Griskevicius et al. 2009), including vaccine choices (Agranov, Elliott, and Ortoleva 2021; Hershey et al. 1994). The effect of social proof has been attributed to conformity (e.g., Cialdini and Goldstein 2004; Cialdini and Trost 1998) and social learning (e.g., Banerjee 1992; Bikhchandani, Hirshleifer and Welch 1992). Conformity suggests that people 'jump the bandwagon' as they derive positive utility from aligning their behavior with perceived social norms (Huh, Vosgerau, and Morewedge 2014). Likewise, social learning plays a crucial role in psychological development. By imitating others, individuals acquire knowledge and skills more efficiently than through self-experimentation, while also minimizing the potential for harmful errors. The instinct for imitation is deeply ingrained and evolutionarily advantageous in

many species (Baddeley 2010). Rather than solely promoting conformity or social learning, in our context, we argue that a social proof nudge can effectively reduce uncertainty by providing reassurance similar to a proxy trial experience.

We now incorporate the social proof nudge. Consider that a proportion $\theta \in [0,1]$ of the population is vaccinated. When a higher proportion is vaccinated, consumers have a higher utility to vaccinate ($\bar{u}$) due to conformity and social learning. In addition, consumers are expected to feel more assured and the perceived uncertainty of side effects ($\delta$) is expected to become smaller. We assume $\delta$ decreases with an increasing population vaccination rate i.e., $\delta(\theta) = \delta \times (1 - \theta)$.

Apart from this positive effect, the social proof nudge can negatively affect vaccine uptake. When a higher proportion is vaccinated, the chance of infection $p$ decreases due to herd immunity (Vitiello et al. 2021). Communicating vaccination rates close to or above a herd immunity threshold (~70-90% with immunity; Rubin 2020) can reduce willingness to vaccinate due to free-riding (Betsch, Böhm, and Korn 2013; Hershey et al. 1994). If consumers behave strategically due to the herd immunity effect and engage in free-riding, the marginal utility for vaccinating decreases with an increasing population vaccination rate. Every consumer has a threshold $\bar{\theta} \in [0, 1]$ above which there is a negative net benefit to vaccinate. In other words, $\bar{\theta}$ is the threshold above which consumers prefer not to vaccinate. We assume the utility function is prudent i.e., $u'''(x) > 0$, a standard assumption in health economics (Eeckhoudt and Gollier 2005).

***Proposition:*** *When the herd immunity effect is small, with an increasing population vaccination rate,*

*(i) an EU consumer will exhibit less aversion to adopting a new technology vaccine compared to a traditional technology vaccine;*

*(ii) if the consumer processes probabilities non-linearly using an inverse-s shaped weighting function, then for small probability of infection p<p*, there will be a greater increase in the uptake of a new relative to a traditional technology vaccine.*

We illustrate this with simulations by assuming a small herd immunity effect in Figure 2. At a low population vaccination rate, the marginal utility to vaccinate is lower for a new than a traditional technology vaccine. As the population vaccination rate increases, willingness to vaccinate increases more strongly for a new than for a traditional technology vaccine (see slope). In addition, aversion to a new technology vaccine is stronger when consumers overweight small probabilities ($\alpha$ = .4, right side) than when processing them linearly ($\alpha$ = 1, left side).

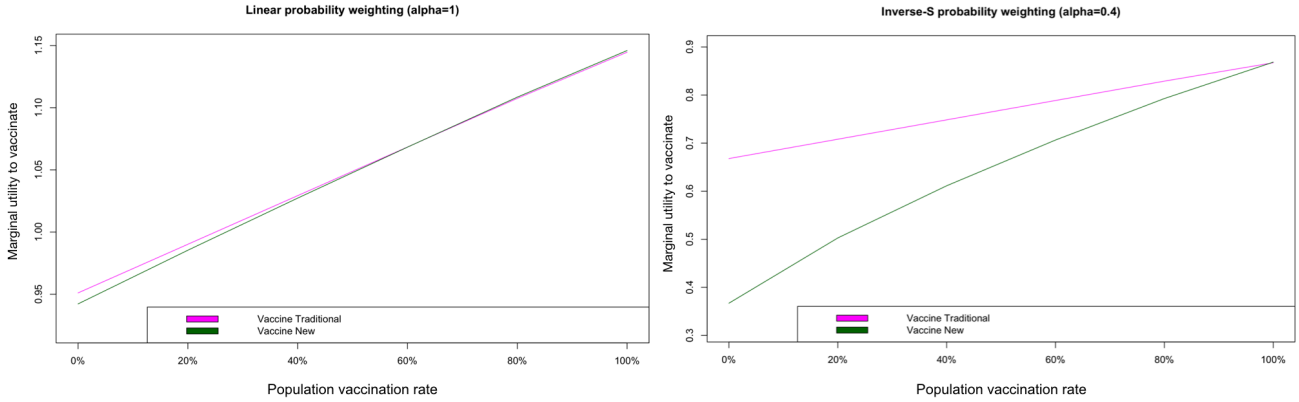


**Figure 2.** Marginal utility to vaccinate with linear (left) and inverse-s shaped Prelec probability weighting with $\alpha = .4$ (right) at different levels of population vaccination rate (Parameters: h = 200, l = 120, $E_N$= .85, $E_T$ = .85 u(x) = $x^{.5}$, c = 40, p(0) = .25, p($\theta$) =.9 - .001$\theta$ (small herd immunity effect), q = .1, $\beta$ = .49, $\bar{u}$ = .2$\theta$ (utility for herd behavior), $\delta_N = 35, \delta_T = .5$)

At a 0% population vaccination rate, when the weighting function is linear, $U_N$ is lower than $U_T$ by 0.009 units. When the weighting function is inverse-s shaped ($\alpha$ = .4), $U_N$ is lower than $U_T$ by 0.3 units, indicating that overweighting of small probabilities of severe consequences increases the efficacy premium. However, adoption of the new technology vaccine accelerates

more rapidly with increasing $\theta$ when the weighting function is inverse-s shaped. In web appendix figure W1, we show that the difference between $U_N$ and $U_T$ decreases when the utility is less concave (i.e., lower risk aversion leads to lower premium).

Due to residual uncertainty that remains for a new compared to a traditional technology vaccine, the perceived herd immunity threshold is lower for a new than for a traditional vaccine when both have the same efficacy. Lemma 3 formalizes this. We illustrate Lemma 3 with simulations in web appendix figure W2.

***Lemma 3.*** *When $E_N = E_T$, the perceived herd immunity threshold of a new technology vaccine is lower than of a traditional technology vaccine.*

Based on the predictions of the model, we can formulate the following hypotheses.

Main effect of new technology vaccine aversion (based on Lemma 1 and Lemma 2i):

***H1:*** *Consumers prefer a traditional over a new technology vaccine due to higher perceived uncertainty about side effects of the latter and require higher vaccine efficacy to compensate.*

Trust in government can affect the perceived uncertainty of side effects of a new vis-à-vis traditional technology vaccine i.e., the difference $\delta_N - \delta_T$, leading to our next hypothesis.

***H2a:*** *Individual factors that amplify perceived uncertainty about side effects of a new compared to a traditional technology vaccine, such as lower trust in government, increase aversion to a new technology vaccine.*

We allow for individual-level variation in preference for the new technology vaccine using the $\epsilon$ term. One factor that could affect $\epsilon$ is TR. When individuals are high in TR, $\epsilon$ is high. Therefore, consumers are expected to have lower aversion to new versus traditional technology vaccines. This leads to our next hypothesis.

***H2b:*** *Individuals with higher TR are less averse to a new technology vaccine than those with lower TR, irrespective of the perceived uncertainty of side effects.*

Reducing new technology aversion with a social proof nudge (based on Proposition i and ii):

***H3a:*** *An increasing population vaccination rate increases willingness to vaccinate more strongly for a new technology vaccine, leading to reduced aversion. This effect is mediated by a decrease in perceived uncertainty about side effects of a new technology vaccine.*

***H3b:*** *Risk averse consumers with stronger overweighting of small probabilities of severe outcomes, will show stronger aversion to a new technology vaccine; the social proof nudge is more effective among those consumers in reducing aversion to a new technology vaccine.*

From Lemma 3, it follows that:

***H4:*** *The perceived herd immunity threshold of a new technology vaccine is lower than of a traditional technology vaccine of similar efficacy. Willingness to vaccinate decreases with an increasing population vaccination rate above the perceived herd immunity threshold.*

## Methodology and Empirical Results

We test these hypotheses in four studies (and five supplementary studies in the web appendix) using hypothetical and semi-consequential/behavioral outcomes, in different populations (US residents recruited via CloudResearch, UK residents recruited via Prolific, international students). We received IRB approval and provide the survey materials in OSF.[3]

[3] OSF link: https://osf.io/rqg93/?view_only=c334036eba2d454e9ea8c0794c3e99ec

In the first three studies, we operationalize the technology as follows: new mRNA technology vs. traditional viral vector technology. We say that Vaccine N is devised from a new technology that has not been used before for vaccine development. This new mRNA technology uses messenger ribonucleic acid created in a laboratory to teach cells how to make a protein that triggers an immune response. We say that Vaccine T is devised from a traditional technology that has been used in many vaccines before. This established technology uses a modified version of a different virus (viral vector) to trigger an immune response.[4] Study 3 is a conceptual replication in four non-vaccine contexts characterized by high uncertainty with a chance of health loss, limited trial possibility and opportunity for free-riding.

***Study 1a: Aversion to New Technology Vaccines***

Study 1a tests H1, that consumers prefer a traditional over a new technology vaccine due to higher perceived uncertainty of side effects of the latter and require higher vaccine efficacy to compensate. We quantified the aversion to the new technology vaccine with an efficacy premium. We argue (in line with Lemma 1 and 2i) that those who are more concerned about side effects of a new technology vaccine have a higher efficacy premium. We also test H2a that those with lower trust in government and regulatory processes tend to have a higher efficacy premium because the perceived uncertainty of side effects is amplified for these individuals.

*Method*

A sample of one-hundred twenty U.K. residents recruited via Prolific ($M_{age}$ = 36.99, SD = 13.51, range: 18-75 years) completed an online survey about potential COVID-19 vaccines. Sample characteristics (and U.S. census data) for all studies are available in table 1.

[4] A pilot test (N = 80, web appendix supplementary study 1) confirmed the new technology was perceived more uncertain than the traditional technology vaccine in terms of side effects. Vaccine efficacy was evaluated correctly (i.e., in line with the provided information).

**Table 1.** Samples reflect a wide range of relevant factors.

| | Study 1a | Study 1b | Study 2 | Study 3 | US Census |
|---|---|---|---|---|---|
| **Age** | | | | | |
| 18-29 years | 36% | 9% | 18% | 14% | 12.40% |
| 30-44 years | 36% | 52% | 51% | 52% | 35.50% |
| 45-59 years | 22% | 28% | 22% | 25% | 32.70% |
| ≥60 years | 7% | 11% | 9% | 9% | 19.40% |
| **Gender** | | | | | |
| Male | 30% | 51% | 53% | 47% | 49.20% |
| Female | 69% | 49% | 46% | 52% | 50.80% |
| **Race and Ethnicity** | | | | | |
| White | 83% | 76% | 73% | 72% | 60.40% |
| Black | 2% | 10% | 12% | 12% | 13.40% |
| Latinx | 0% | 1% | 4% | 7% | 18.30% |
| Asian | 8% | 5% | 6% | 6% | 5.90% |
| Mixed | 4% | 3% | 3% | 2% | 2.70% |
| **Education** | | | | | |
| High School/GED or less | 40% | 12% | 11% | 8% | 29% |
| Some College | - | 17% | 16% | 14% | 16% |
| Associates or Technical Degree | 3% | 10% | 13% | 9% | 4% |
| Bachelor Degree | 45% | 39% | 41% | 45% | 22% |
| Graduate or Professional Degree | 11% | 21% | 17% | 22% | 12% |
| **Income** | | | | | |
| <$25,000 | 27% | 11% | 15% | 11% | 17.4% |
| $25,000 - $49,999 | 32% | 23% | 24% | 21% | 18.7% |
| $50,000 - $74,999 | 23% | 23% | 24% | 25% | 16.2% |
| $75,000 - $99,999 | 14% | 21% | 17% | 19% | 11.9% |
| $100,000 - $149,999 | 3% | 12% | 10% | 14% | 15.9% |
| ≥$150,000 | 1% | 8% | 7% | 7% | 19.9% |

*Note:* Education and income from the U.K. sample (study 1a) were converted approximately to U.S. equivalents from https://www.census.gov/en.html.

After providing consent and completing a filter question regarding previous COVID-19 infection,[5] participants answered questions regarding COVID-19 risk perception which we used

[5] Study 1a was conducted in the COVID-19 context. Vaccines were not widely available at this point. We excluded participants with immunity through infection. In all other studies, we measured COVID-19 vaccination status at the end as a control variable.

as control variables (risk covariate: "*What do you think is your chance of getting infected with COVID-19 during the next 3 months?*", severity covariate: "*What do you think would be your chance of becoming severely ill, if you were to be infected with COVID-19?*", life impact covariate: "*How much would it affect your personal and/or professional life, if you were to be infected with COVID-19?*" 1 = not at all, 7 = very much). Next, participants were informed about a traditional and a new technology vaccine as described above. The new technology was described as having a 90% efficacy, while the traditional technology had a 70% efficacy in preventing severe cases of the disease. Both vaccines were described as having *no serious safety concerns*. As a first dependent variable, participants rated their willingness to vaccinate for each of the vaccines ("*How willing would you be to receive this vaccine?*" 1 = not at all, 7 = very much). We allowed participants to have a direct comparison of the vaccine types, mirroring the decisions consumers face when evaluating COVID-19 vaccines.[6]

This was followed by a vaccination trade-off task to elicit the efficacy premium for the traditional versus new technology vaccine. We provided a choice list in which the efficacy of the traditional technology vaccine increased in five-point increments (from 55% to 99%, in an ascending order), while the efficacy of the new technology vaccine was constant (90%). Participants indicated their preference for ten choice sets (new technology vaccine with 90% efficacy, indifferent, traditional technology vaccine with x% (= 55% to 99%) efficacy).

Next, participants indicated how concerned they were about side effects of the traditional and new technology vaccine as a mediator ("*How worried are you about potential side effects of the Traditional/New Technology Vaccine?*"). As a moderator, we measured trust in government ("*How much trust do you have in your government that they can handle COVID-19 well"*") and

[6] According to the Centers for Disease Control and Prevention, people can choose, depending on age, which vaccine type to receive: https://www.cdc.gov/coronavirus/2019-ncov/vaccines/faq.html

confidence in the regulatory process ("*How confident are you about the regulatory process that has given a temporary emergency approval to the vaccines?*" all items: 1 = not at all, 7 = very much). We averaged the two last items to a trust score. We also asked whether participants regularly took flu shots as a control variable (yes, no). Finally, participants answered questions about age, gender, residency, education, income, occupation, front line worker status and ethnicity.

*Results*

***Willingness to vaccinate***. We compared willingness to vaccinate with the traditional vs. new technology using a paired samples t-test. Despite the fact that the new technology vaccine was described as 20% more effective, there was no difference in willingness to vaccinate ($M_{trad}$ = 5.41, $M_{new}$ = 5.40, t(119) = .075, $p$ = .939, d = .006). Further, participants were more concerned about the side effects of the new than the traditional technology vaccine ($M_{trad}$ = 3.03, $M_{new}$ = 3.85, t(119) = -8.63, $p$ < .001, d = -.787). In line with H1, this suggests participants require significantly higher efficacy to compensate for concerns about side effects of a new technology vaccine.

***Efficacy premium.*** The efficacy premium (M = 19.11, SD = 14.62) was significantly larger than zero (t(114) = 14.01, $p$ < .001, d = 1.30), indicating a considerable degree of aversion to new technology. In line with H1, participants were, on average, willing to trade off 19.11% in efficacy for avoiding the new technology vaccine. Figure 3 shows the cumulative distribution. On the x-axis, values above zero represent the degree to which individuals are willing to sacrifice vaccine efficacy for receiving a traditional instead of new technology vaccine (i.e., new technology aversion). Values below zero indicate the extent to which individuals are willing to sacrifice vaccine efficacy for receiving a new over a traditional technology vaccine. Values around zero indicate no willingness to trade off vaccine efficacy. The y-axis shows the proportion of

participants with an efficacy premium of utmost the specific value. Figure 3 displays significant variation because the probability mass is not clustered around a single value or a narrow range.

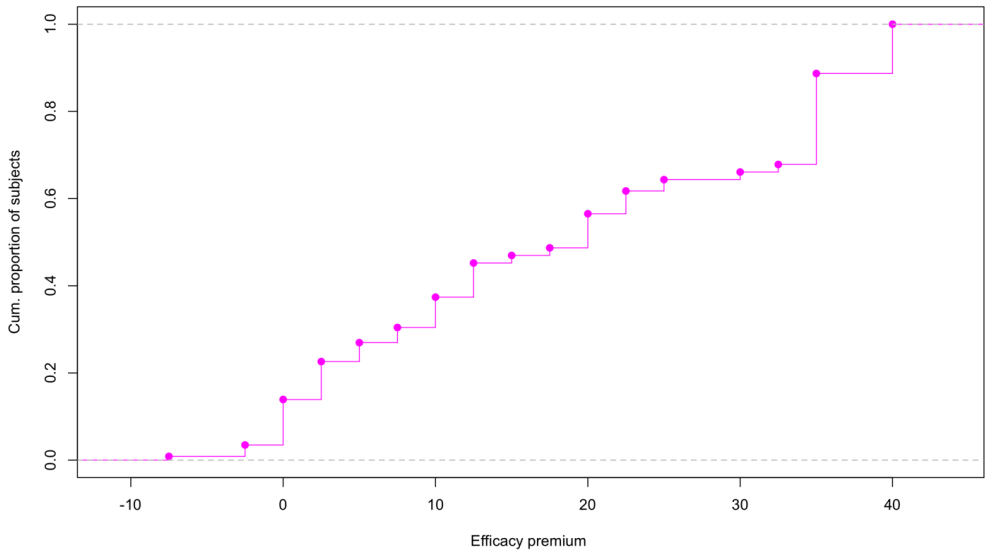


**Figure 3.** Cumulative proportion of participants with different efficacy premia.

***Mediation***. To test H2a, we conducted mediation analysis (Hayes' PROCESS macro, Model 4 with 5,000 bootstrap samples; Hayes 2017) predicting the efficacy premium with trust in government via concern about side effects (see Figure 4). Consistent with our model assumption that $\delta_N - \delta_T$ increases with lower trust, those with lower trust were more concerned about the side effects of the new vis-à-vis traditional technology vaccine (b = -.22, SE = .06, $CI_{95}$ = [-.34, -.10], $p < .001$). Higher concern about side effects of the new vis-à-vis traditional technology vaccine led to a higher efficacy premium (b = 4.65, SE = 1.19, $CI_{95}$ = [2.31, 6.98], $p < .001$). The relationship between trust and the efficacy premium was mediated via concern about side effects (Indirect effect: b = -1.01, SE = .46, $CI_{95}$ = [-1.93, -.30], $p < .001$), supporting H2a (see web appendix table W1 for OLS regression with controls). A correlation matrix is available in web appendix table W2.

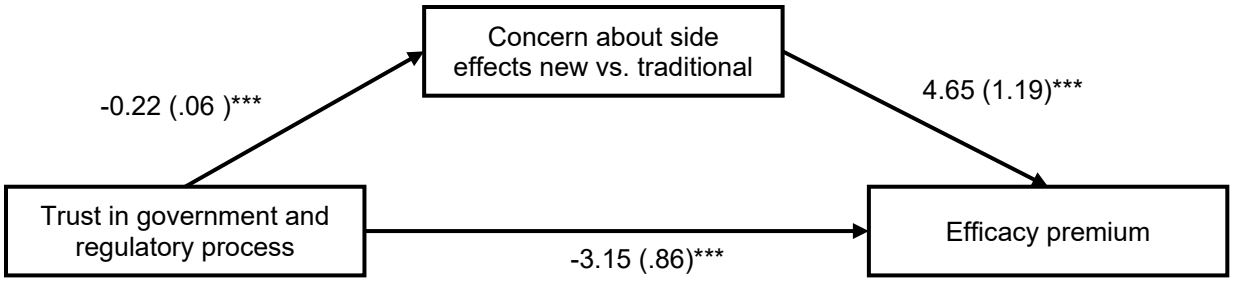


**Figure 4.** Concern about side effects mediates the relationship between trust in government and the efficacy premium.

*Discussion*

Study 1a shows that consumers are more averse to vaccinate with a new than a traditional technology vaccine, even if it is described as more effective. On average, participants were willing to trade-off 19% in efficacy for avoiding a new technology vaccine (supporting H1). Additionally, we offer support for H2a. Individuals with lower trust in government and regulatory processes were more concerned about side effects of the new technology vaccine (vis-à-vis traditional technology vaccine), and therefore required a higher efficacy premium.

***Study 1b: Conjoint Analysis of New Technology Aversion***

In this study, we provide a more stringent test of H1 by replacing the choice list with conjoint methodology which is also used in vaccine research (e.g., Kreps et al. 2020). We changed the U.K. COVID-19 context and investigated general vaccine preference in a U.S. sample. We quantify the impact of several vaccine attributes on preferences and further explore heterogeneity in vaccine preferences due to trust in government and TR (H2a and H2b).

*Method*

We recruited a sample of N = 438 US adults ($M_{age}$ = 43.37, SD = 11.78, range: 19-77 years) via Amazon Mechanical Turk using CloudResearch's Approved List to ensure high data quality (Litman, Robinson, and Abberbock 2017). We conducted a power analysis based on a

two dependent means comparison using t-tests. Using G*Power 3.1 (Faul et al. 2009), we estimated a sample size requirement of n = 412 on an anticipated minimum detectable effect size of 0.178 (from a pilot test) at a power of 0.95 and a type-I error of 0.05. This sample size is in line with a commonly used conjoint analysis formula (n > 500c/(t x a); Orme 2010).

We employed a factorial conjoint methodology with three attributes: vaccine technology (new mRNA vs. traditional viral vector), efficacy level (60% vs. 90%), and uncertainty of side effects (0.1% chance of *severe* side effects and 99.9% chance of no side effect vs. 100% chance of *mild* to *moderate* side effects). We varied the uncertainty of side effects to examine how a small possibility of severe side effects could influence vaccine preference compared to the certainty of a 100% chance of mild to moderate side effects. All attributes were varied in a 2 x 2 x 2 factorial design, requiring eight evaluations from each participant. This allowed us to quantify the effect of the technology, while controlling for different levels of efficacy and uncertainty of side effects.

Participants were informed about a new, highly infectious viral disease. They assumed to be unvaccinated, and that the government had provided emergency approval for several vaccines which varied in terms of three factors. These were described in more detail (web appendix figure W3 and table W3). Participants evaluated eight vaccines, presented randomly (*How likely are you to get this vaccine?* 1 = extremely unlikely, 7 = extremely likely). We also elicited willingness to pay (*How much would you be willing to pay for this vaccine?* Scale: $0 - $200).

Participants completed several individual difference measures as moderators (presented randomly). We included the 16-item TRI 2.0 index (Parasuraman and Colby 2015) which measures propensity to adopt and embrace technology. We obtained a segment classification of our sample into low, medium, and high tiers of TR based on US normative data.[7] We measured trust in

[7] https://rockresearch.com/techqual/. TRI 2.0 is copyrighted by Rockbridge Associates and A. Parasuraman. We obtained written permission from the authors to use the scale for academic purposes.

government (*How much trust do you have in your government that they can handle a health crisis well?* 1 – 7 scale) and trust in science, using the six-item Credibility of Science Scale (Hartman et al. 2017). The latter was included to distinguish between different information sources (politicians vs. scientists) which could reduce perceived uncertainty and thus increase adoption of new technology vaccines. Lastly, participants completed questions about demographics (i.e., age, gender, income, education, ethnicity, occupation) and vaccine status (i.e., regular flu shot, number of COVID-19 vaccinations, whether they had received an mRNA vaccine) as control variables.

*Results*

As each participant provided eight evaluations, we performed the analyses on 3,504 ratings. We used panel regression analysis predicting willingness to vaccinate with three vaccine attributes (technology: base is traditional technology, efficacy: base is 60%, uncertainty of side effects: base is 100% mild to moderate side effects). Standard errors are clustered at the individual level. The results, including models with different controls, are shown in table 2.

***Main outcomes.*** All vaccine attributes had a significant effect on willingness to vaccinate. As predicted by H1, willingness to vaccinate was significantly lower (b = -.316, $p < .001$) for new than traditional technology vaccines, even when controlling for efficacy and side effects, thus demonstrating aversion to new technology vaccines. Willingness to vaccinate was higher for 90% efficacy (b = 1.174, $p < .001$) than for 60% efficacy and lower for vaccines with a small chance of severe side effects (than for 100% chance of mild/moderate side effects, b = -.123, $p < .001$). Results remain equivalent when adding demographics (model 2, table 2) and general vaccine controls (model 3, table 2). This indicates that participants were averse to new technology vaccines, even after controlling for side effects and efficacy. Given the regression parameters, labelling a vaccine as new versus traditional had an equivalent effect as reducing vaccine efficacy

by around 8.07%. The vaccine technology had around 2.56 times the effect as changing the side effects from 100% mild/moderate to a 0.1% chance of severe side effects. The results of the same panel regression with willingness to pay were largely identical. Participants were willing to pay less for a new technology vaccine (web appendix table W4).

**Table 2.** Efficacy must compensate for uncertainty of side effects and newness of technology.

| | Dependent Variable<br>Willingness to Vaccinate | | |
|---|---|---|---|
| | Model 1 | Model 2 | Model 3 |
| New Technology | -.316***<br>(.046) | -.324***<br>(.047) | -.324***<br>(.047) |
| 90% Efficacy | 1.174***<br>(.055) | 1.166***<br>(.056) | 1.166***<br>(.056) |
| Severe side effects | -.123***<br>(.032) | -.122***<br>(.033) | -.122**<br>(.033) |
| Gender (Female) | | -.146<br>(.144) | -.154<br>(.121) |
| Age | | .007<br>(.005) | -.008<br>(.005) |
| Income | | .197***<br>(.052) | .022<br>(.043) |
| White/Caucasian | | -.148<br>(.166) | -.077<br>(.143) |
| Nr. of COVID-19 vaccines received | | | .537***<br>(.051) |
| No regular flu shot | | | -.292**<br>(.132) |
| Constant | 4.020***<br>(.077) | 3.270***<br>(.314) | 3.325***<br>(.371) |
| Observations | 3504 | 3424 | 3424 |
| $R^2$ | .092 | .116 | .270 |
| Adjusted $R^2$ | .092 | .115 | .268 |
| Residual Std. Error | 1.917 (df = 3500) | 1.885 (df = 3416) | 1.713 (df = 3414) |
| F Statistic | 118.628***<br>(df = 3; 3500) | 64.233***<br>(df = 7; 3416) | 140.500***<br>(df = 9; 3414) |

*Note: *p < .1; **p < .05; ***p < .01*

To quantify the magnitude of aversion to new technology vaccines at the individual level, we subtracted each participant's average willingness to vaccinate for the new technology from the willingness to vaccinate for the traditional technology vaccines. We call this the willingness to vaccinate premium.[8] Positive values indicate preference for traditional technology vaccines and aversion to new technology. On average, the premium was positive (M = .31, SD = .95) and significantly different from zero ($t(437) = 6.9$, $p < .001$, d = .33), supporting H1. We find a similar pattern for the willingness to pay premium (web appendix figure W4 and W5 for the cumulative distributions). To test H2a and H2b, we regressed the willingness to vaccinate premium on the individual difference measures.

***Trust in government.*** Trust in government was significantly associated with the premium (b = -.104, $p < .001$). Those with higher trust in government showed less aversion to new technology vaccines. The negative association remained significant when including demographics and general vaccine controls (regular flu shot, number of COVID-19 vaccinations), providing support for H2a (web appendix table W5). Trust in science, on the other hand, was not associated with the premium (b = -.017, $p = .490$). Consumers seem to be averse to new technology vaccines as they mistrust the political system when promoting a public health agenda, rather than scientists.

***TR.*** Based on normative data from Rockbridge, individuals were segmented into low (17%), medium (26.5%) and high (56.4%) TR tiers. We show a non-linear relationship between TR and the willingness to vaccinate premium (web appendix table W6). Compared to the low TR tier, the medium tier had a significantly lower premium (or aversion to new technology, b = -.329, $p = .020$), supporting H2b. Including demographics and general vaccine controls did not impact

[8] We also calculated an efficacy premium as in study 1a. For each individual, we calculated the increase in efficacy that would compensate for the lower willingness to vaccinate for the new technology vaccine. The results showed a similar pattern as for the willingness to vaccinate premium. The average efficacy premium within-subject was 6.65%. This was significantly higher than zero ($p < .001$).

the results. In the high TR segment, there was no further reduction of the premium, possibly due to a ceiling effect. Willingness to vaccinate in this segment was very high for both vaccines.

*Discussion*

Studies 1a and b show that many consumers, especially those with low trust in government and low TR, prefer a traditional over a new technology vaccine and require higher efficacy to compensate for the perceived uncertainty of side effects. Next, we test whether and how a social proof nudge—communicating increasing population vaccination rates—can reduce this aversion.

***Study 2: Social Proof Nudge Reduces New Technology Aversion***

Study 2 tests H3a, that a social proof nudge increases willingness to vaccinate more strongly for a new technology vaccine. We also hypothesized that a reduction in perceived uncertainty of side effects of new technology vaccines (rather than conformity or social learning) mediates the relationship between the social proof nudge and aversion to new technology vaccines. We measured TR, trust in government, and risk preferences as moderators. To capture potential free-riding and test hypothesis H4, we also measured herd immunity considerations.

*Method*

We recruited N = 738 US adults ($M_{age}$ = 40.41, SD = 11.75, range: 19-76 years) via from Amazon Mechanical Turk using CloudResearch (Litman, Robinson, and Abberbock 2017). Study 2 was a pre-registered[9] 2 x 4 full-factorial between-subjects experiment to reduce the possibility of demand effects (Shimp, Hyatt, and Snyder 1991). We varied the technology (new vs. traditional) and the population vaccination rate (social proof nudge: 0%, 30%, 60% vs. 90% vaccinated). See web appendix supplementary study 2 and 3 for within-subjects designs. Based on Giner-Sorolla

[9] https://aspredicted.org/fx6m6.pdf

(2018), we quadrupled the sample size obtained in G*Power to achieve 80% power of an interaction in a 2 x 4 ANOVA design with 3 degrees of freedom and medium effect size.

Participants read about a new and highly infectious viral disease and that they were unvaccinated. After seeing this information, they rated their likelihood of contracting the disease, severity of symptoms if contracting the disease (both items: 1–7 slider scale), and how much they would be willing to pay for a health insurance package which did *not* include vaccines (scale: $0–$2,000). These items were used as control variables.

Next, participants read information about two equally effective vaccines (traditional technology and new technology, as previously). Participants were told the government would decide which vaccine was offered to them. Participants were then randomized into eight conditions, varying the vaccine technology and the social proof nudge as follows: "*The government has decided to provide Vaccine T* (traditional technology condition) */ Vaccine N* (new technology condition) *in your area. 0%* (vs. *30%, 60%,* or *90%*) *of the population have decided to vaccinate with Vaccine T (Vaccine N) so far."*

Participants rated the likelihood to vaccinate with the respective vaccine they had been assigned to (*"How likely are you to get vaccinated with vaccine T* (in the traditional technology condition) */ vaccine N* (in the new technology condition)*?"* 1 = not likely at all, 7 = very likely). We also elicited willingness to pay for a health insurance package which included the respective vaccine they had been assigned to (*"How much would you be willing to pay per month for a health insurance package which includes the traditional / new technology vaccine without additional cost?"* Scale: $0-$2,000).

To quantify the aversion to the new vis-a-vis traditional technology vaccine, participants imagined that the traditional (vs. new) technology vaccine was provided for free in their health

insurance package. But they could pay an additional amount to switch to the other vaccine (*"How much would you be willing to pay to switch to the new / traditional technology vaccine?"* Scale: $0–$100). We refrained from providing a scale that went below zero as getting paid to receive a particular vaccine might be perceived as unethical, leading to reactance.

As mediator for the effect of the social proof nudge, we measured perceived uncertainty of side effects (*"How uncertain do you think are the side effects of vaccine T / N?"*). As alternate mediators, we captured social learning ("*How knowledgeable do you think others are about the vaccination choice compared to you?"*) and conformity ("*Do you think others would judge you for NOT getting vaccinated with the traditional (new) technology vaccine?")*. All items were measured on a 1 – 7 scale. To measure herd immunity considerations (Galizzi et al. 2022), we asked *"What percentage of your environment do you think need to get the new (traditional) technology vaccine to protect those who do not get vaccinated against this disease?"* (scale: 0% - 100% of the population).

To measure risk preference, we used a bisection method commonly employed in decision analysis (Wakker and Deneffe, 1996). Participants completed four hypothetical monetary gambles. In the first gamble, to elicit overweighting of small probabilities, participants made several choices where a lottery ($100 with 5% chance, $0 with 95% chance) was compared to a sure payoff. Initially, the sure payoff was set to $5 (i.e., the expected value of the lottery). Depending on participants' choices, the sure payoff amount was adjusted dynamically. If a participant selected the lottery in the first choice, the sure payoff amount was increased to $52.5 (i.e., midpoint between $5 and $100). Subsequently, if participants chose the lottery again in the next round, they were presented with a choice between the lottery and a higher sure payoff amount (i.e., $76.25, the midpoint between $52.5 and $100). This process continued, with participants making a maximum

of four choices to determine the indifference point between the lottery and a specific sure payoff amount (also known as certainty equivalence). A higher certainty equivalence indicates risk seeking and overweighing of small probabilities (under linear utility). In the second and third gamble, the certainty equivalences were elicited by changing the probabilities to medium and high values. In the fourth gamble, we elicited risk preferences for monetary losses by (hypothetically) endowing participants with $100. Participants indicated their preference between a 50% chance of losing $100 and different sure losses until an indifference point was determined.

As previously, participants completed the TRI 2.0 and rated their trust in the government as moderators. Finally, participants answered demographics and general vaccination control items.

*Results*

***Willingness to vaccinate.*** The distribution of willingness to vaccinate was bimodal with two distinct peaks (web appendix figure W6) at the extreme points (lowest point: 16.12%, highest point: 15.99%). To appropriately analyze the data, instead of OLS, we used the least-absolute value model (or median regression) as it is more robust to non-normal data, less sensitive to outliers, and has no assumptions about the distribution of the parameters (Yu, Lu, and Stander 2003).

Willingness to vaccinate was significantly lower in the new (Med = 4.17, SD = 2.28) than the traditional technology condition (Med = 5, SD = 2.05, t = 3.01, $p$ = .003), thus replicating aversion to new technology vaccines (H1). To test H3a, we ran a median regression predicting willingness to vaccinate with the technology (base: traditional), the population vaccination rate dummies (base: 0%) and their interaction. At the 0% population vaccination rate, willingness to vaccinate was lower in the new than the traditional technology condition (b = -1.50, $p$ = .003), indicating aversion to new technology. At higher population vaccination rates, this difference

became less prominent (30%: $p = .040$, 60%: $p = .154$, 90%: $p = .060$). The results were consistent when controlling for demographics and COVID-19 vaccination status (see table 3).

**Table 3.** Aversion to new technology decreases with increasing social proof nudge.

| | Dependent variable: Willingness to vaccinate | |
|---|---|---|
| | Model 1 | Model 2 |
| New Technology Condition | -1.50*** | -.880** |
| | (.511) | (.369) |
| Social Proof Nudge – 30% | 1.00** | .794** |
| | (.506) | (.367) |
| Social Proof Nudge – 60% | 1.06** | .646* |
| | (.508) | (.371) |
| Social Proof Nudge – 90% | 1.11** | 1.087*** |
| | (.511) | (.370) |
| New Technology x 30% Social Proof Nudge | 1.48** | .274 |
| | (.718) | (.516) |
| New Technology x 60% Social Proof Nudge | 1.03 | .924* |
| | (.721) | (.521) |
| New Technology x 90% Social Proof Nudge | 1.37* | .825 |
| | (.72) | (.521) |
| Gender (Female) | | -.014 |
| | | (.185) |
| Age | | 8.67e-19 |
| | | (.007) |
| Income | | .0004 |
| | | (.065) |
| White/Caucasian | | -.39 |
| | | (.212) |
| Nr. of COVID-19 vaccines received | | 1.012*** |
| | | (.070) |
| Constant | 4.00*** | 1.919*** |
| | (.362) | (.490) |
| Observations | 738 | 713 |
| Pseudo $R^2$ | .051 | .221 |

*Note: *p < .1; **p < .05; ***p < .01*

***Willingness to pay.*** We see similar results for the willingness to pay for a health insurance package including the new vs. traditional technology vaccine. Since this variable was positively skewed (skewness = 1.65, kurtosis = 5.01), we performed a log transformation. At the 0% population vaccination level, willingness to pay was significantly lower by $76.53 per month in the new than the traditional technology condition (b = -.786, $p$ = .010), controlling for demographics, flu, and COVID-19 vaccination status. At higher population vaccination rates, this difference became non-significant (web appendix table W7).

***Willingness to pay to switch.*** Next, we investigate the willingness to pay to switch the vaccine type included in the health insurance package. Our data showed a peak at zero, indicating that the variable was censored. Therefore, we ran a tobit regression with left censoring at zero (Tobin 1958). At the 0% population vaccination rate, participants were willing to pay a premium of $16.87 in the new technology condition (to switch to the traditional vaccine, b = 16.87, $p$ = .034), controlling for baseline willingness to pay for health insurance. Participants in the new technology condition reduced their willingness to pay to switch when the population vaccination rate increased from 0% to 60% compared to the traditional technology condition (b = -22.46, $p$ = .044). When a higher percentage of the population was vaccinated with the new technology vaccine, participants were less inclined to pay a premium to switch to the traditional vaccine (web appendix table W8). These results provide support for H3a.

***Mediation***. To test our proposed uncertainty reduction mechanism, we conducted mediation analysis (PROCESS Model 4; 5,000 bootstrapped samples; Hayes 2017), estimating the indirect effect of the social proof nudge on willingness to vaccinate through perceived uncertainty of side effects in the new technology condition. We jointly added uncertainty of side effects, the social learning and conformity items as mediators (see Figure 5). The social proof nudge reduced

perceived uncertainty of side effects (b = -.21, SE = .08, $CI_{95}$[-.37, -.05]) and perceived uncertainty of side effects reduced willingness to vaccinate in the new technology condition (b = -.49, SE = .06, $CI_{95}$[-.61, -.37]). Supporting our predicted process, the mediating effect of perceived uncertainty was significant (b = .10, SE = .04, $CI_{95}$[.03, .19]). This indicates that the social proof nudge reduced uncertainty of side effects of the new technology vaccine, which resulted in higher willingness to vaccinate. The measures of social learning and conformity[10] had no mediating effect (social learning indirect effect: b = -.02, SE = .001, $CI_{95}$[-.08, .02]; conformity indirect effect: b = -.004, SE = .01, $CI_{95}$[-.03, .02]. In the traditional technology condition, there was no mediation.

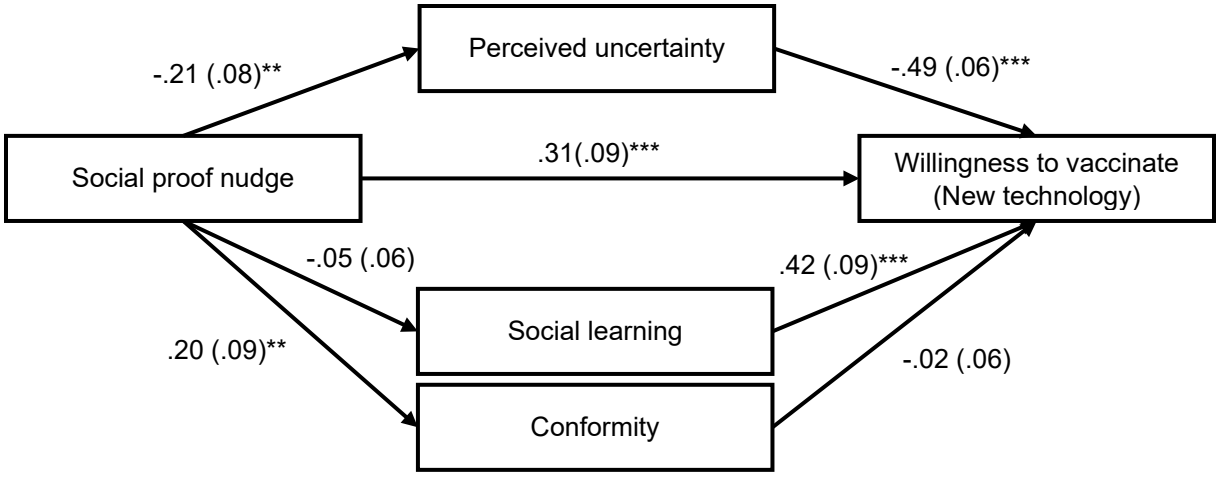


**Figure 5.** Perceived uncertainty is a mediator in the new technology condition.

***Herd immunity considerations***. We next test H4, that the perceived herd immunity threshold is lower for a new than a traditional technology vaccine. The herd immunity threshold was lower in the new (M = 62.26, SD = 28.60) than the traditional technology condition (M = 67.00, SD = 25.72, t(763) = 2.37, $p$ = .018, d = .17). There was no main effect or interaction with the social proof nudge ($p$ = .225 and $p$ = .877, respectively). When calculating the difference between the (manipulated) population vaccination rate and each participant's perceived herd

[10] With increasing population vaccination rate, participants felt more judged by others for their vaccination choice ($p$ < .001). This was independent of the vaccine technology (interaction: $p$ = .54, main effect technology: $p$ = .57).

immunity threshold, a higher difference was associated with lower willingness to vaccinate (b = -.012, $p < .010$). These results confirm H4 and indicate there are strategic free-riding considerations above a herd immunity threshold. Free-riding considerations begin earlier for the new technology vaccine due to a lower perceived herd immunity threshold. Regression results are shown in web appendix table W9. To investigate TR, trust in government and risk preferences, we performed median regressions predicting willingness to vaccinate with the two manipulated factors (technology, social proof nudge), the moderators, and their interactions.

***TR.*** There was an interaction between the technology condition and TR (b = 1.06, $p = .008$, web appendix table W10). In the new (but not traditional) technology condition, participants with a higher TR score had higher willingness to vaccinate. Also, mid and high TR tiers had lower aversion to the new technology vaccine compared to the low tier (mid-tier: b = 1.73, $p = .069$; high tier: b = 1.75, $p = .045$, web appendix table W11). The high TR tier also tended to pay less to switch from the new to traditional technology vaccine (b = -16.14, $p = .001$, web appendix table W12), supporting H2b. TR was not associated with uncertainty of side effects ($p$s = ns). Even when controlling for uncertainty of side effects, participants in the mid and high TR tier were more willing to vaccinate with the new technology (mid: b = 1.79, $p = .029$; high: b = 1.87, $p = .012$). Thus, high TR consumers seem to embrace the inherent uncertainty of new technology vaccines.

***Trust in government.*** Higher trust in government was associated with lower perceived uncertainty of side effects. This association was stronger in the new technology condition. In the traditional technology condition, a one-unit increase in trust in government was associated with an uncertainty reduction by -.145 ($p = .007$). In the new technology condition, trust was associated with an *additional* -.137 ($p = .064$) reduction. Table 4 shows the regression for TR (model 1) and trust in government (model 2) predicting perceived uncertainty of side effects.

**Table 4**. Greater trust in government yields less concern about side effects.

| | Dependent variable: Uncertainty of side effects | |
|---|---|---|
| | Model 1 | Model 2 |
| New Technology Condition | .979** | 1.083*** |
| | (.407) | (.305) |
| Social Proof Nudge - 30% | -.419** | -.356** |
| | (.184) | (.181) |
| Social Proof Nudge - 60% | -.541*** | -.491*** |
| | (.185) | (.182) |
| Social Proof Nudge - 90% | -.470** | -.467** |
| | (.186) | (.183) |
| TR medium tier | -.036 | |
| | (.337) | |
| TR high tier | -.438 | |
| | (.309) | |
| New Technology x TR medium tier | -.749 | |
| | (.480) | |
| New Technology x TR high tier | -.294 | |
| | (.439) | |
| Trust in government | | -.141*** |
| | | (.054) |
| New Technology x Trust in government | | .132* |
| | | (.074) |
| Age | -.002 | -.002 |
| | (.006) | (.006) |
| Gender (Female) | .235* | .290** |
| | (.132) | (.129) |
| Income | .033 | .026 |
| | (.049) | (.048) |
| Education | -.101* | -.041 |
| | (.057) | (.057) |
| White/Caucasian | .215 | .203 |
| | (.151) | (.148) |
| Constant | 5.120 *** | 5.133 *** |
| | (.462) | (.411) |
| Observations | 710 | 710 |
| $R^2$ | .067 | .094 |
| Adjusted $R^2$ | .050 | .080 |
| Residual Std. Error | 1.730 (df = 696) | 1.702 (df = 698) |
| F Statistic | 3.850*** (df = 13; 696) | 6.620*** (df = 11; 698) |

*Note: *p < .1; **p < .05; ***p < .01*

***Risk preferences.*** Surprisingly, risk preferences elicited via monetary gambles did not predict vaccine preferences. This might have been due to two reasons: First, we elicited risk preferences for monetary rather than health outcomes, but domain specificity might matter (Soane and Chmiel 2005). Second, according to our model, risk aversion for small probability losses (rather than gains like we measured) predicts the new technology vaccine premium. In supplementary study 4, we investigate risk aversion for health losses. Those with higher risk aversion (i.e., for small probability of health loss) showed stronger aversion to a new vis-à-vis traditional technology vaccine. With an increasing social proof nudge, risk averse individuals were more confident about the new technology vaccine and more willing to adopt, confirming H3b.

***Study 3: Conceptual Replication***

In study 3, we replicate our findings in four non-vaccine contexts which share the characteristics of new technology vaccines (i.e., high stakes with a potential health loss, limited trial possibility, threat of free-riding). The new technologies were the following: 1) a novel treatment for bacterial infections: Stem Cell-Derived Antimicrobial Peptides (Kumar et al. 2021) instead of traditional antibiotics, 2) pesticides employing nano-technology (Wang et al. 2022) instead of conventional pesticides, 3) lithium-ion battery instead of traditional gas engine cars and 4) hydrogen energy (Scovell 2022) instead of conventional gas heating. All stimuli were adapted from real-world articles. The new technologies were described as having benefits over the traditional technologies but also potential health risks and externalities that can lead to free-riding (see OSF for wording). We also included semi-consequential/behavioral outcome measures. We expected to see aversion to the new technologies and a reduction thereof by a social proof nudge due to a lowering of perceived uncertainty. TR, trust in government, and risk aversion were expected to be moderators.

*Method*

MTurk workers recruited via CloudResearch (N = 500; $M_{age}$ = 40.94 years, SD = 11.75, range: 20 – 75 years) participated in this study. We conducted a power analysis based on a linear multiple regression (fixed model, single regression coefficient). Using G*Power 3.1 (Faul et al. 2009), we estimated a sample size requirement of n = 395 for an anticipated minimum detectable effect size $f^2$ of 0.02 at a power of 0.8, a type-I error of 0.05 and six predictors (three dummies for product context, three dummies for the social proof nudge).

Participants saw four product categories. For each product category, participants were randomly assigned to view one of four social proof nudges (0%, 30%, 60%, 90% adoption of new technology product, more details below). To obtain a direct measure of new technology aversion, instead of manipulating the new technology between-subjects, participants saw both the traditional and new technology and indicated their preference between them (slider scale: 0 to 100). Values below the midpoint 50 indicated aversion to the new technology; values above the midpoint indicated preference for the new technology; the midpoint 50 indicated indifference. For all product categories, participants could also select if they wanted neither of the two options. This represents real-world product choices more realistically as consumers typically have a direct comparison of options with a possibility not to purchase. For all products, as a mediator variable, we measured perceived uncertainty of the new technology compared to the traditional technology (*"Please rate how risky you think this technology is."* 1 = less risky, 7 = more risky).

*Product 1:* For the pharma product, participants imagined they were sick from a contagious bacterial infection. Their doctor told them about two treatments to stop the infection and contagion: a traditional antibiotic and a new non-antibiotic technology based on stem cell-derived antimicrobial peptides. Both treatments were described in terms of benefits and risks. This was

followed by the social proof nudge (e.g., if assigned to the 0% condition: *"None (0%) of patients with this bacterial infection in your area have tried the new non-antibiotic technology"*). Participants indicated their preference on a slider scale (*"Which treatment would you prefer?"* 0 = prefer traditional antibiotic, 50 = indifferent, 100 = prefer new non-antibiotic technology). Participants could then sign up to a mailing list to receive a brochure about the non-antibiotic technology (1 = yes, 0 = no) and provided their email address.

*Product 2*: For the pesticide, participants imagined their living area was heavily infested by insects. A salesperson in the hardware store recommended two products to stop the infestation: a traditional pesticide and a new nano-enabled pesticide. Both pesticides were described in terms of risks and benefits, and the social proof nudge was presented (e.g., if assigned to the 30% condition: *"30% of the residents in your area have chosen the new nano-enabled pesticide"*). Participants answered the same product preference question and mediator question as for the first product. Participants could then download an article with more information about nano-pesticides (1 = yes, 0 = no), and were provided with a link redirecting them to an article.

*Product 3*: For the car context, participants viewed information about a conventional gas engine and a lithium-ion battery car, followed by the social proof nudge (e.g., if assigned to the 60% condition: "*60% of recent car buyers in your area have chosen a lithium battery car"*). Participants answered the same product preference and mediator question as for the previous products. Participants could then view a map with electric fueling stations for lithium battery cars. We embedded this interactive map[11] in the survey and measured the time spent on the page.

[11] https://afdc.energy.gov/stations/#/find/nearest

*Product 4*: For the energy context, participants read information about conventional gas heating and a new hydrogen heating technology. After seeing the social proof nudge (e.g., if assigned to the 90% condition: "*90% of homeowners in your area have chosen a new hydrogen technology system"*), they answered the same product preference and mediator question as for the previous products. Participants could then sign up to a mailing list to receive a brochure about the new hydrogen heating technology.

As moderators, we measure risk preferences, TR, and trust in government. We included a single-item measure of risk seeking which highly correlates with risk preferences in lab setting (Dohmen et al. 2011) and has been used extensively in health economics (Decker and Schmitz 2016) ("*Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?*" scale: 0 - 10). Higher values indicate more risk seeking (less risk aversion).

To test H3b that overweighting of small probabilities of (or risk aversion to) extreme losses leads to larger aversion to new technology, we elicited risk preferences for small probabilities. The method was based on literature in health economics (Attema, L'Haridon, and van de Kuilen 2019) as all products contained a potential health loss. Participants read a scenario in which they suffered from a disease expected to reduce life expectancy by 20 years. There were two equally effective treatments. Treatment A had a 2% chance of losing 10 years and a 98% chance of losing 5 years; Treatment B had a 2% chance of losing 15 years and a 98% chance of losing 4 years and 11 months. Although the expected value of both treatments is equal, treatment B with extreme outcomes is riskier than Treatment A. We asked which treatment they would prefer (A, indifferent, B).

We measured trust in government ("*How much trust do you have in your government that they can regulate new technology well?*" 1 = none at all, 7 = a lot), and TR using a shortened 6-item version of the TRI 2.0 (Parasuraman and Colby 2015) as well as demographics as previously.

*Results*

***Preference ratings.*** First, we look at the preferences across all product categories (2,000 ratings of 500 participants). In 20.3% (406) of cases, participants wanted neither option (bacterial treatment: 19.8%, pesticide: 29.7%, car: 15.6%, heating: 16.2%, web appendix table W13). We analyzed 79.7% of ratings where participants expressed a preference between the products.

The average preference rating was lower than 50 (indifference point), indicating significant aversion to the new technologies. Although participants were surprisingly averse to the new technologies on average, this aversion decreased when increasing the population adoption rate. We show this by running an OLS regression (with clustered standard errors) controlling for product context (web appendix table W14). On average, the social proof nudge increased preference for the new technology at all levels (0% vs. 30%: b = 7.93, $p < .001$, 0% vs. 60%: b = 14.81, $p < .001$, 0% vs. 90%: b = 18.7, $p < .001$), even when controlling for demographics. Not only at the aggregate level, but also for each product category, participants showed significant aversion to the new technology, which was reduced by the social proof nudge. Figure 6 shows the product preferences across social proof nudge conditions for all product contexts.

***Mediation***. In all product categories, perceived uncertainty was reduced by the social proof nudge. Separate mediation analyses (PROCESS Model 4; 5,000 bootstrapped samples; Hayes 2017) for each product category yielded significant indirect effects of the social proof nudge on product preference via perceived uncertainty. Table W15 in the web appendix shows the descriptive statistics across conditions, the main effect of the social proof nudge and the indirect effect via perceived uncertainty for each product category.

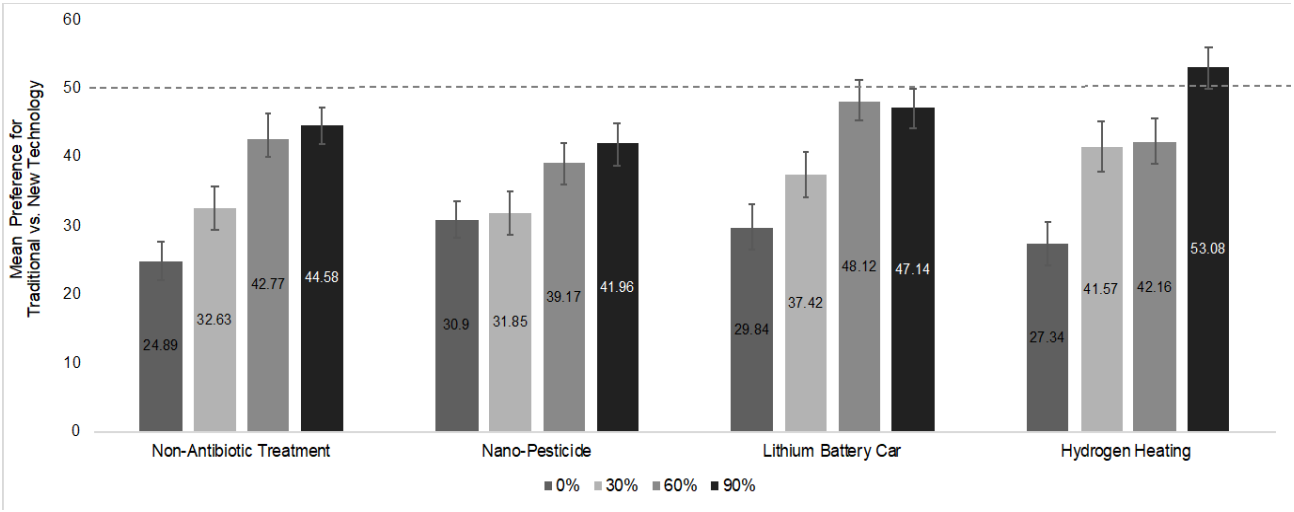


**Figure 6.** Mean preference for the new technology vis-à-vis traditional technology option.

Notes: Error bars = +/- 1 SE. Indifference point between both options is indicated by the dashed line.

***Secondary outcomes***. We saw a similar, albeit weaker pattern as to be expected for semi-consequential and behavioral outcomes. To increase statistical power, we treated the social proof nudge as an ordinal predictor rather than three dummy variables. For the non-antibiotic treatment, every 30% increase in the social proof nudge increased the odds of sign-up to a mailing list by 23% (logit regression: b = .206, $p$ = .043, web appendix table W16). Similarly, every 30% increase in the social proof nudge increased the odds of wanting to download an article about nano-pesticides by 30% (logit regression: b = .264, $p$ = .027, web appendix table W17). For the lithium battery car, we measured the time spent on the interactive map of electric fueling stations as a behavioral proxy. We found a marginally significant effect of the social proof nudge. With increasing social proof, participants spent more time on the map (linear regression: b = 7.22, $p$ = .070, web appendix table W18). For the hydrogen heating, we found no effect on sign-up to a mailing list (logit regression: b = .209, $p$ = .163, web appendix table W19), possibly because participants had already been asked a similar question for the non-antibiotic treatment.

Controlling for demographics, social proof nudge, and product context, we analyze the role of trust in government, TR score (and tiers), and risk aversion on product preference. We find similar evidence at the level of each product category (correlation table W20 in the web appendix).

***Trust in government.*** Across all products on average, trust in government was positively associated with the preference rating (b = 4.84, $p < .001$), indicating less aversion to new technology with higher trust (web appendix table W21). Trust in government was also negatively associated with the perceived uncertainty of the new technology (b = -.17, $p < .001$). Higher perceived uncertainty in turn decreased preference for the new technology (b = -13.13, $p < .001$).

***TR.*** The TR score was positively associated with the preference rating (b = 8.62, $p < .001$), indicating less aversion to new technology with higher TR (web appendix table W22). Similarly, the mid-tier (b = 9.93, $p = .002$) and high tier (b = 14.96, $p < .001$) had a higher preference rating than the low TR tier (web appendix table W23).

***Risk preferences.*** Self-reported risk-seeking was positively associated with the preference for the new technology (b = 2.62, $p < .001$, web appendix table W24). Similarly, when looking at risk aversion for small probabilities, participants who chose treatment B (i.e., more risky treatment) tended to have a higher preference rating than participants who were indifferent ($p = .026$) or who chose treatment A (i.e., less risky treatment, $p = .031$, web appendix table W25).

*Discussion*

These results replicate our previous findings in four non-vaccine contexts with similar characteristics (i.e., high stakes with potential health loss, limited trialability, threat of free-riding). Consumers, especially those with lower trust in government, lower TR, and higher risk aversion, are surprisingly averse to new technologies. A social proof nudge reduces this aversion by lowering the perceived uncertainty associated with new technologies.

## General Discussion

In this research, we explored consumer perceptions of technological innovations in high-uncertainty environments with health losses, limited trialability, and threat of free-riding (such as vaccine decision making). We find that consumers are surprisingly averse to vaccines described as employing new technology and require higher vaccine efficacy (during the peak of the COVID-19 pandemic, 19% higher efficacy) to compensate for greater perceived uncertainty of side effects. Vaccines described as employing new technology seem to be second choice for many when compared to traditional vaccines, even if they are described as more effective in preventing a disease and as having no serious safety concerns. We found considerable heterogeneity in aversion to new technology. Distrust in government exacerbates this aversion, while TR diminishes it. In addition, risk-averse consumers who overweight small probabilities avoid new technology vaccines more. For those consumers, traditional technology vaccines are more attractive alternatives, unless policy-makers can reduce the perceived uncertainty of side effects of new technology vaccines, for example with social proof nudges.

Communicating an increasing population vaccination rate reduces vaccine hesitancy more strongly for new than for traditional technology vaccines, thus effectively reducing aversion to new technology. Our process evidence indicates, for new technology vaccines, social proof lowers the perceived uncertainty of side effects, similar to a proxy trial experience, rather than by prompting conformity or social learning as previous research has shown (Campbell and Fairey 1989; Cialdini and Goldstein 2004; Goldstein, Cialdini, and Griskevicius 2008; Deutsch and Gerard 1955). Individuals with a tendency to overweight small probabilities of severe consequences, respond more positively to the social proof nudge as it reduces this uncertainty.

Communicating population vaccination rates close to or higher than a herd immunity threshold can reduce vaccination uptake due to free-riding (Hardin 1968; Ostrom et al. 1999). Survey research has found that about 6% of respondents classify themselves as vaccination free-riders (Parker et al. 2013). We find evidence of free-riding above an individual's perceived herd immunity threshold and that free-riding is more pronounced for new technology vaccines due to a lower perceived herd immunity threshold. However, on average, the free-riding effect was not strong enough to outweigh the positive effect of social proof. Finally, we show these findings are likely to hold for other products with similar characteristics, such as non-vaccine pharmaceuticals, nano-technology pesticides, lithium battery cars and hydrogen energy. We found a significant degree of new technology aversion (and reduction thereof by means of a social proof nudge).

Our findings have practical implications for marketers when promoting new technologies. For product innovations that share the same characteristics that we investigated, marketers should tailor their communication strategy to different consumer segments. For consumers with low trust in government, low TR, and a strong tendency to overweight small probabilities, leveraging social proof can be an effective strategy to speed up adoption. On the other hand, individuals with high trust in government, high TR and no propensity to overweight small probabilities may not require social proof nudges for fast adoption. In fact, in this segment, social proof may even lead to free-riding and potentially slow down adoption. Marketers can identify these segments based on proxies such as willingness to pay for insurance premiums, past purchases of high-tech products and demographics related to TR such as age and education level (Parasuraman and Colby 2015). By understanding these distinctions, marketers can create targeted campaigns that resonate with specific segments, driving successful adoption of new technologies at a faster pace.

Marketers should employ different communication strategies depending on the extent to which new technologies align with the characteristics we explored. For innovations that have the potential for free-riding but allow a certain degree of trial (e.g., test-driving a lithium battery car), marketers should prioritize making trial experiences widely available and sharing customer testimonials. When the potential for free-riding is high (e.g., energy-efficient products with high switching costs), marketers should elicit consumers' equivalent to a perceived herd immunity threshold for the new technology and avoid communicating adoption rates above this threshold.

When a technology does not allow trial, and the risk of free-riding is low (e.g., AI controlled medical procedures, mRNA vaccines against cancer; Fiedler et al. 2016), social proof can be a cornerstone of marketing communication. An application is the promotion of new technology treatments via social media. While social media platforms have drawn negative attention for spreading medical misinformation and conspiracy theories (Wilson and Wiysonge 2020), social media can be leveraged to communicate increasing uptake and reduce uncertainty (for example with micro influencers; Bonnevie et al. 2020).

When a technology's greatest need lies in communities with severe distrust (e.g., new technology pesticides for farmers in rural areas, HIV pre-exposure prophylaxis for sex workers in developing countries), marketers should understand the root-causes of distrust, seek feedback to address concerns and focus on reducing the perceived uncertainty associated with new technologies in a transparent fashion, as exaggerated claims may contribute to further distrust.

We would like to mention some ethical considerations when nudging individuals to adopt new technology. In our manuscript, we implicitly assume that the new technology is beneficial, and that the benefits outweigh the risks. In many real-life situations, this trade-off is often not as straightforward (see for example in the COVID-19 vaccine context, Dag Berild et al. 2022;

Fraiman et al. 2022; Sun, Jaffe, and Levi 2022). Risks might also vary depending on individual characteristics (e.g., individuals with impaired immune systems, or pregnancy). Policy-makers and marketers must carefully consider the potential (unknown, long-term) risks of new technology and respect the autonomy of decision makers as social proof nudges might bias information processing in ways that lead consumers to overlook uncertainty when they should not. The decision to adopt new technology can be construed as a function of individual beliefs traits (e.g., TR, trust) which can be considered "system 1" or more instinctual variables (Morewedge and Kahneman 2010), and information observable in the marketplace (e.g., risk information, adoption rates). Consumers should be mindful of their personal predispositions and biases and approach the provided information from a neutral perspective, whilst also checking the validity of social proof claims.

Our research has limitations. We derived our prediction based on a static model. Future research should examine how consumers dynamically update attitudes over time based on others' adoption and observed outcomes. We predominantly investigated US residents (studies 1b-3). However, we believe our findings are applicable widely since we replicated our findings in the UK (study 1a, web appendix study 1 & 2) and with international students (web appendix study 3). Future research should also explore the exact process(es) through which social proof reduces perceived uncertainty of new technology (e.g., higher confidence, narrowing of confidence interval of risk estimates; Sedlmeier and Gigerenzer 1997). We used self-reported willingness to vaccinate which may differ from actual behavior. But, there is evidence that self-reports correlate considerably with vaccine uptake (Lehmann et al. 2014). We also included semi-consequential/behavioral measures in study 3 (e.g., sign-up to receive information about new technology, downloading an article) and found consistent results. Nevertheless, conducting large-scale randomized experiments on actual choices would be the gold standard.

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