Check for updates

DOI: 10.1177/00222429231220295

Author Accepted Manuscript

JOURNAL of Marketing

Adoption of New Technology Vaccines

Journal:	*Journal of Marketing*
Manuscript ID	JM-22-0323.R3
Manuscript Type:	Revised Submission
Research Topics:	Adoption of Innovations, Food and Health, Health Care Marketing , Public Policy and Marketing, Behavioral Decision Theory, Behavioral Economics
Methods:	Choice Models, Online Experiments, Regression Models, Analysis of Variance

SCHOLARONE™
Manuscripts

Author Accepted Manuscript

Adoption of New Technology Vaccines

Laura Zimmermann, Assistant Professor of Marketing, IE Business School, Madrid, Spain, laura.zimmermann@ie.edu

Jeeva Somasundaram, Assistant Professor of Decision Sciences, IE Business School, Madrid, Spain, jeeva.somasundaram@ie.edu

Barsha Saha, Assistant Professor of Information Systems and Analytics, Jindal Global Business School, O.P. Jindal Global University & Indian Institute of Management Shillong, India, barsha.saha@jgu.edu.in

Author(s) Note: The first and second author contributed equally to the manuscript.

Acknowledgement: We would like to thank Amitav Chakravarti and Luc Wathieu for their valuable feedback on previous versions of this manuscript. We used ChatGPT to refine specific sections of the manuscript's language.

Financial Disclosure: Research reported in this manuscript was partially funded by AEI - 10.13039/501100011033 Grant No. PID2019-111512RB-I00 and MCIN /AEI /10.13039/501100011033 / FEDER, UE Grants No PID2022-138729OA-I00.

Peer Review Version

Author Accepted Manuscript

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

Peer Review Version

Author Accepted Manuscript

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

Peer Review Version

Author Accepted Manuscript

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

Peer Review Version

Author Accepted Manuscript

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

Peer Review Version

Author Accepted Manuscript

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.

Peer Review Version

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 βq. 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 δ 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.

Author Accepted Manuscript

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 δ, 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.

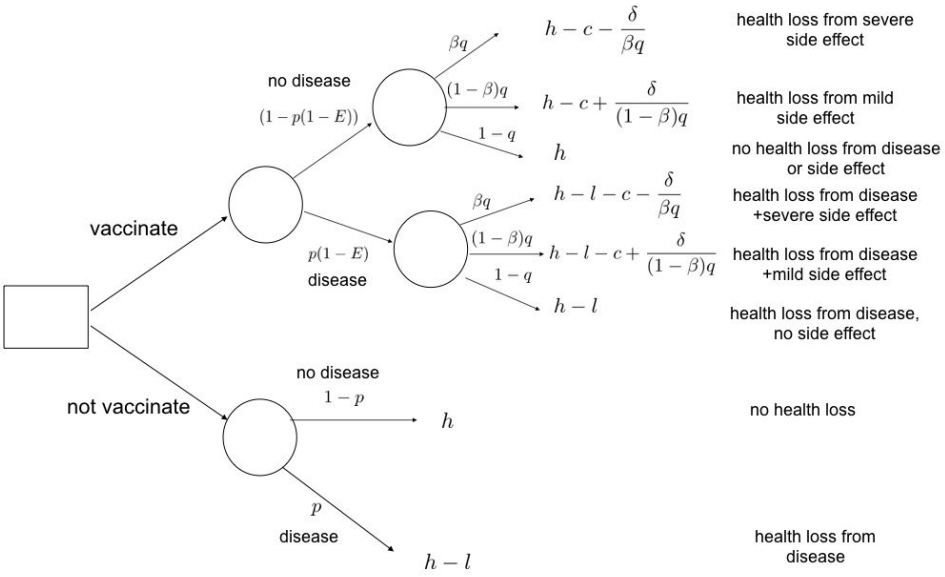


Figure 1. Decision tree capturing health outcomes.

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 δ is higher, the variance of side effects (σ^2) is higher. Since the average side effect is c, higher variance implies a higher coefficient of variation (σ/μ) which captures uncertainty in a statistical sense.

Author Accepted Manuscript

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 δ or more variance in side effects) than the traditional technology vaccine. We indicate δ for the new technology by δ_N and for the traditional technology by δ_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

Author Accepted Manuscript

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 (δ) 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

Peer Review Version

Author Accepted Manuscript

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 ϵ 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 ϵ 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.

Peer Review Version

Author Accepted Manuscript

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 α 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*

Peer Review Version

Author Accepted Manuscript

(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 α (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

Peer Review Version

Author Accepted Manuscript

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 (δ) is expected to become smaller. We assume δ 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 $\overline{\theta} \in [0, 1]$ above which there is a negative net benefit to vaccinate. In other words, $\overline{\theta}$ 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;

Peer Review Version

Author Accepted Manuscript

(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 (α = .4, right side) than when processing them linearly (α = 1, left side).

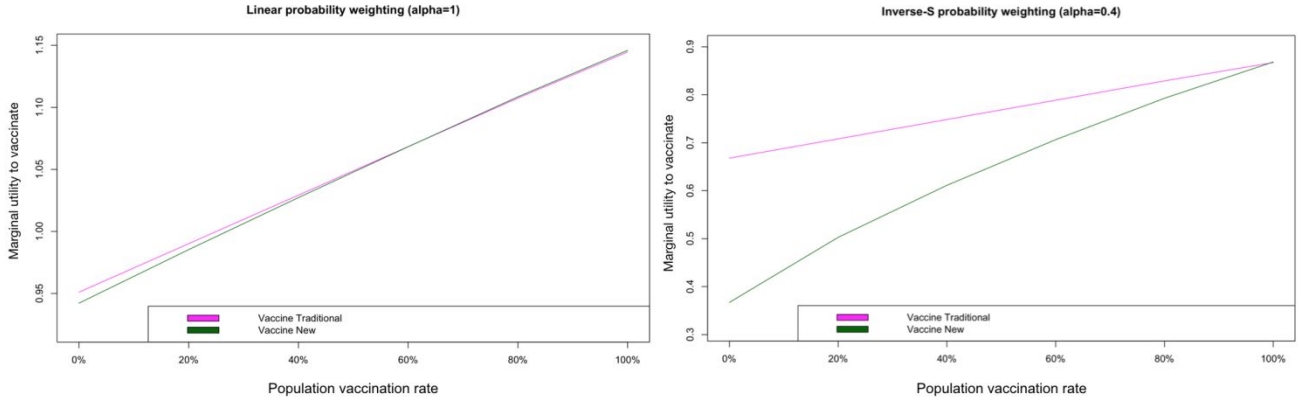


Figure 2. Marginal utility to vaccinate with linear (left) and inverse-s shaped Prelec probability weighting with $\alpha = .4$ (right) at different levels of population vaccination rate (Parameters: h = 200, l = 120, E_N= .85, E_T = .85 u(x) = $x^{.5}$, c = 40, p(0) = .25, p(θ) =.9 - .001θ (small herd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

Author Accepted Manuscript

more rapidly with increasing θ 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 ϵ term. One factor that could affect ϵ is TR. When individuals are high in TR, ϵ is high. Therefore, consumers are expected to have lower aversion to new versus traditional technology vaccines. This leads to our next hypothesis.

Peer Review Version

Author Accepted Manuscript

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.*

Peer Review Version

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

Author Accepted Manuscript

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).

Peer Review Version

Author Accepted Manuscript

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.

Peer Review Version

Author Accepted Manuscript

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 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).

[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.

[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

Peer Review Version

Author Accepted Manuscript

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 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

Peer Review Version

Author Accepted Manuscript

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.

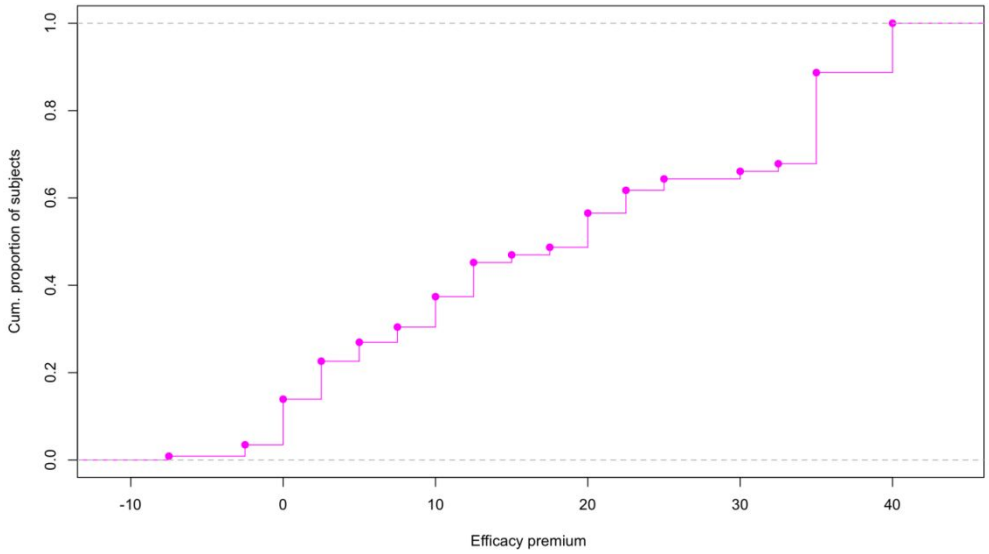


Figure 3. Cumulative proportion of participants with different efficacy premia.

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

Version

Author Accepted Manuscript

appendix table W1 for OLS regression with controls). A correlation matrix is available in web appendix table W2.

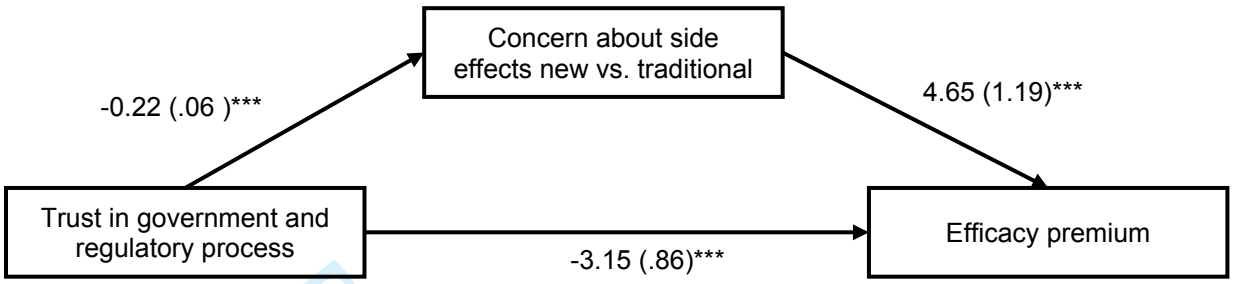


Figure 4. Concern about side effects mediates the relationship between trust in government and the efficacy premium.

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

Peer Review Version

Author Accepted Manuscript

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

Peer Review Version

Author Accepted Manuscript

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 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, $p < .001$).

[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.

Peer Review Version

Author Accepted Manuscript

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 Willingness to Vaccinate		
	Model 1	Model 2	Model 3
New Technology	-.316*** (.046)	-.324*** (.047)	-.324*** (.047)
90% Efficacy	1.174*** (.055)	1.166*** (.056)	1.166*** (.056)
Severe side effects	-.123*** (.032)	-.122*** (.033)	-.122** (.033)
Gender (Female)		-.146 (.144)	-.154 (.121)
Age		.007 (.005)	-.008 (.005)
Income		.197*** (.052)	.022 (.043)
White/Caucasian		-.148 (.166)	-.077 (.143)
Nr. of COVID-19 vaccines received			.537*** (.051)
No regular flu shot			-.292** (.132)
Constant	4.020*** (.077)	3.270*** (.314)	3.325*** (.371)
Observations	3504	3424	3424
R^2	.092	.116	.270

Peer Review Version

Author Accepted Manuscript

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*** (df = 3; 3500)	64.233*** (df = 7; 3416)	140.500*** (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.

[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 ($p < .001$).

Peer Review Version

Author Accepted Manuscript

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 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

Author Accepted Manuscript

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 (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

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

Author Accepted Manuscript

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

Peer Review Version

Author Accepted Manuscript

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

Peer Review Version

Author Accepted Manuscript

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***

Peer Review Version

Author Accepted Manuscript

	(.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).

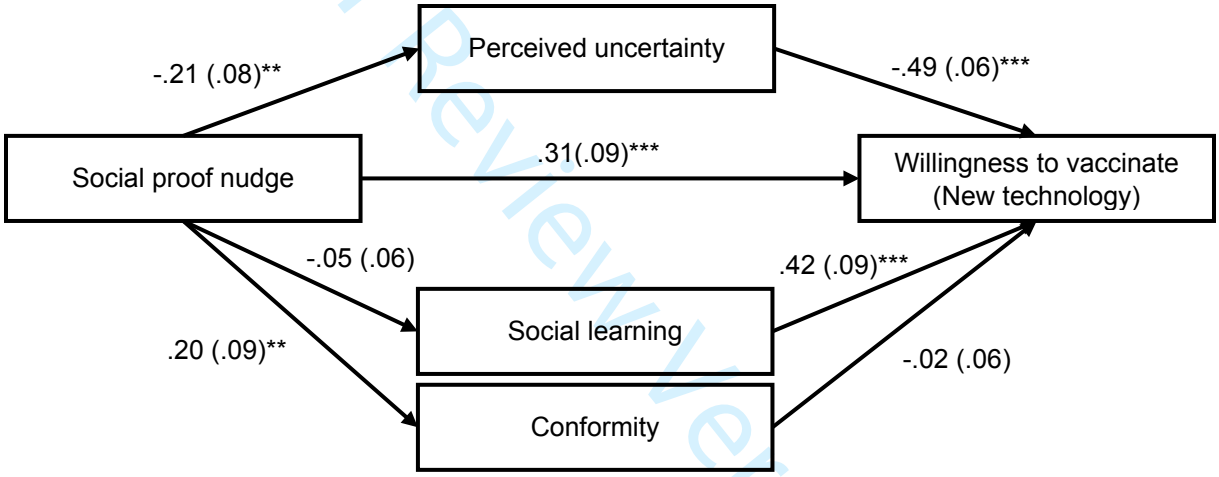
Willingness to pay to switch. Next, we investigate the willingness to pay to switch the vaccine type included in the health insurance package. Our data showed a peak at zero, indicating that the variable was censored. Therefore, we ran a tobit regression with left censoring at zero (Tobin 1958). At the 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

Peer Review Version

Author Accepted Manuscript

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

[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: $p = .57$).

Peer Review Version

Author Accepted Manuscript

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 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 (ps = 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

Peer Review Version

Author Accepted Manuscript

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.

Peer Review Version

Author Accepted Manuscript

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*

Peer Review Version

Author Accepted Manuscript

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.

Peer Review Version

Author Accepted Manuscript

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

Peer Review Version

Author Accepted Manuscript

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

Peer Review Version

Author Accepted Manuscript

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.

Peer Review Version

Author Accepted Manuscript

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.

Peer Review Version

Author Accepted Manuscript

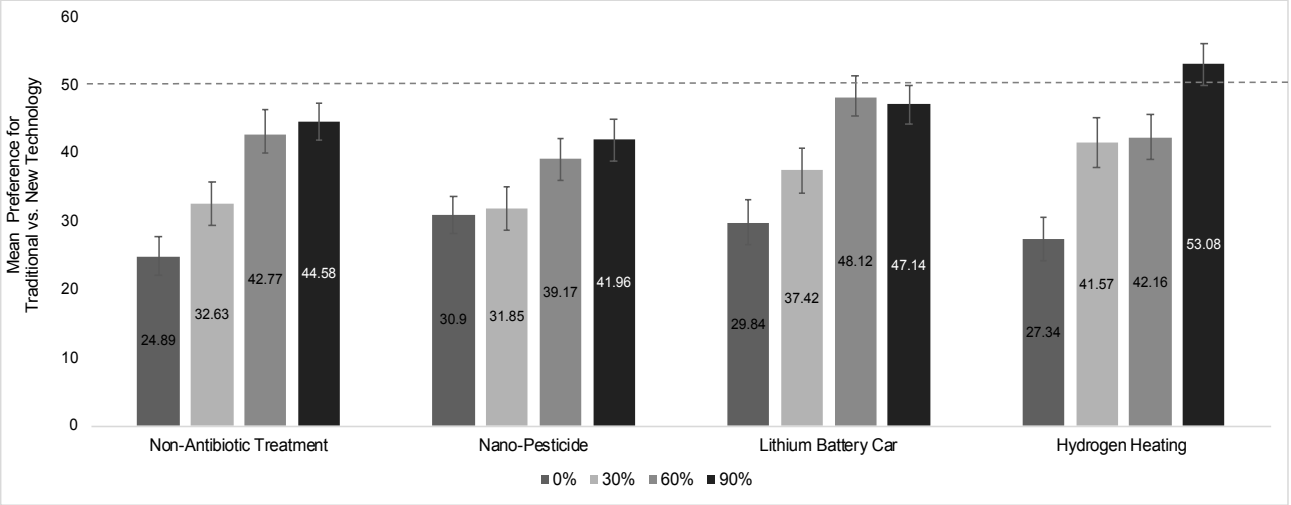


Figure 6. Mean preference for the new technology vis-à-vis traditional technology option.

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.

For Review Version

Author Accepted Manuscript

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.

Peer Review Version

Author Accepted Manuscript

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.

Peer Review Version

Author Accepted Manuscript

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.

Peer Review Version

Author Accepted Manuscript

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;

Peer Review Version

Author Accepted Manuscript

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.

Peer Review Version

Author Accepted Manuscript

References

Agranov, Marina, Matt Elliott, and Pietro Ortoleva (2021), "The importance of Social Norms against Strategic Effects: The case of Covid-19 vaccine uptake," *Economics Letters*, 206, 109979.

Attema, Arthur E., Olivier L'Haridon, and Gijs van de Kuilen (2019), "Measuring multivariate risk preferences in the health domain," *Journal of Health Economics*, 64, 15–24.

Baddeley, Michelle (2010), "Herding, social influence and economic decision-making: socio-psychological and neuroscientific analyses," *Philosophical Transactions of the Royal Society B: Biological Sciences*, 365 (1538), 281–90.

Banerjee, Abhijit V. (1992), "A Simple Model of Herd Behavior," *The Quarterly Journal of Economics*, 107 (3), 797–817.

Bass, Frank M. (1969), "A New Product Growth for Model Consumer Durables," *Management Science*, 15 (5), 215–27.

Bearden, William O. and Terence A. Shimp (1982), "The Use of Extrinsic Cues to Facilitate Product Adoption," *Journal of Marketing Research*, 19 (2), 229-239.

Betsch, Cornelia, Robert Böhm, and Lars Korn (2013), "Inviting free-riders or appealing to prosocial behavior? Game-theoretical reflections on communicating herd immunity in vaccine advocacy.," *Health Psychology*, 32 (9), 978–985.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch (1992), "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades," *Journal of Political Economy*, 100 (5), 992–1026.

Blut, Markus and Cheng Wang (2020), "Technology readiness: a meta-analysis of conceptualizations of the construct and its impact on technology usage," *Journal of the Academy of Marketing Science*, 48 (4), 649–69.

Bonnevie, Erika, Sarah D. Rosenberg, Caitlin Kummeth, Jaclyn Goldbarg, Ellen Wartella, and Joe Smyser (2020), "Using social media influencers to increase knowledge and positive attitudes toward the flu vaccine," *Plos One*, 15 (10), e0240828.

Campbell, Jennifer D and Patricia J Fairey (1989), "Informational and normative routes to conformity: The effect of faction size as a function of norm extremity and attention to the stimulus.," *Journal of Personality and Social Psychology*, 57 (3), 457–68.

CDC (2023), "How Vaccines are Developed and Approved for Use," https://www.cdc.gov/vaccines/basics/test-approve.html

Cialdini, Robert B. and Noah J. Goldstein (2004), "Social Influence: Compliance and Conformity," *Annual Review of Psychology*, 55 (1), 591–621.

Cialdini, Robert B. (2001), "The Science of Persuasion," *Scientific American*, 284 (2), 76–81.

Cialdini, Robert B. and Melanie R Trost (1998), "Social influence: Social norms, conformity and compliance.," in *The handbook of social psychology, Vols. 1-2, 4th ed.*, New York, NY, US: McGraw-Hill, 151–92.

Courbage, Christophe and Richard Peter (2021), "On the effect of uncertainty on personal vaccination decisions," *Health Economics*, 30 (11), 2937–42.

Crainich, David, Louis Eeckhoudt, and Mario Menegatti (2019), "Vaccination as a trade-off between risks," *Italian Economic Journal*, 455–72.

Dag Berild, Jacob, Vilde Bergstad Larsen, Emilia Myrup Thiesson, Toni Lehtonen, Mari Grøsland, Jon Helgeland, Jan Wolhlfahrt, Jørgen Vinsløv Hansen, Arto A Palmu, and Anders Hviid (2022), "Analysis of Thromboembolic and Thrombocytopenic Events After the AZD1222,

Peer Review Version

Author Accepted Manuscript

BNT162b2, and MRNA-1273 COVID-19 Vaccines in 3 Nordic Countries," *JAMA Network Open*, 5 (6), e2217375–e2217375.

Decker, Simon and Hendrik Schmitz (2016), "Health shocks and risk aversion," *Journal of Health Economics*, 50, 156–70.

Desiraju, Ramarao, Harikesh Nair, and Pradeep Chintagunta (2004), "Diffusion of new pharmaceutical drugs in developing and developed nations," *International Journal of Research in Marketing*, 21 (4), 341–57.

Deutsch, Morton and Harold B Gerard (1955), "A study of normative and informational social influences upon individual judgment.," *The Journal of Abnormal and Social Psychology*, 51 (3), 629–36.

Diaz, Parris, John Zizzo, Navin C. Balaji, Rohit Reddy, Kajal Khodamoradi, Jesse Ory, and Ranjith Ramasamy (2022), "Fear about adverse effect on fertility is a major cause of COVID-19 vaccine hesitancy in the United States," *Andrologia*, 54 (4), e14361.

Dodd, Rachael H, Kristen Pickles, Brooke Nickel, Erin Cvejic, Julie Ayre, Carys Batcup, Carissa Bonner, Tessa Copp, Samuel Cornell, Thomas Dakin, Jennifer Isautier, and Kirsten J McCaffery (2021), "Concerns and motivations about COVID-19 vaccination," *The Lancet Infectious Diseases*, 21 (2), 161–63.

Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G. Wagner (2011), "Individual risk attitudes: Measurement, Determinants, and behavioral consequences," *Journal of the European Economic Association*, 9 (3), 522–50.

Eeckhoudt, Louis and Christian Gollier (2005), "The Impact of Prudence on Optimal Prevention," *Economic Theory*, 26 (4), 989–94.

Faul, Franz, Edgar Erdfelder, Axel Buchner, and Albert-Georg Lang (2009), "Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses," *Behavior Research Methods*, 41 (4), 1149–60.

Feurer, Sven, Steve Hoeffler, Min Zhao, and Michal Herzenstein (2021), "Consumers' response to really new products: A cohesive synthesis of current research and future research directions," *International Journal of Innovation Management*, 25 (08).

Fiedler, Katja, Sandra Lazzaro, Johannes Lutz, Susanne Rauch, and Regina Heidenreich (2016), "mRNA Cancer Vaccines," in *Current Strategies in Cancer Gene Therapy. Recent Results in Cancer Research,* vol 209. Springer, Cham.

Fraiman, Joseph, Juan Erviti, Mark Jones, Sander Greenland, Patrick Whelan, Robert M. Kaplan, and Peter Doshi (2022), "Serious adverse events of special interest following mRNA COVID-19 vaccination in randomized trials in adults," *Vaccine*, 40 (40), 5798–5805.

Freeman, Daniel, Felicity Waite, Laina Rosebrock, Ariane Petit, Chiara Causier, Anna East, Lucy Jenner, Ashley-Louise Teale, Lydia Carr, Sophie Mulhall, Emily Bold, and Sinéad Lambe (2022), "Coronavirus conspiracy beliefs, mistrust, and compliance with government guidelines in England," *Psychological Medicine*, 52 (2), 251–63.

Galizzi, Matteo M., Krystal Lau, Marisa Miraldo, and Katharina Hauck (2022), "Bandwagoning, free-riding and heterogeneity in influenza vaccine decisions: An online experiment," *Health Economics*, 31 (4), 614–46.

Giner-Sorolla, Roger. (2018), "Powering Your Interaction," https://approachingblog.wordpress.com/2018/01/24/powering-your-interaction-2/.

Goldenberg, Jacob, Sangman Han, Donald R. Lehmann, and Jae Weon Hong (2009), "The Role of Hubs in the Adoption Process," *Journal of Marketing*, 73 (2), 1–13.

Goldstein, Noah J., Robert B. Cialdini, and Vladas Griskevicius (2008), "A Room with a

For Peer Review Version

Author Accepted Manuscript

Viewpoint: Using Social Norms to Motivate Environmental Conservation in Hotels," *Journal of Consumer Research*, 35 (3), 472–82.

Griskevicius, Vladas, Noah J. Goldstein, Chad R. Mortensen, Jill M. Sundie, Robert B. Cialdini, and Douglas T. Kenrick (2009), "Fear and Loving in Las Vegas: Evolution, Emotion, and Persuasion," *Journal of Marketing Research*, 46 (3), 384–95.

Hamel, Liz, Ashley Kirzinger, Cailey Muñana, and Mollyann Brodie (2020), "KFF COVID-19 Vaccine Monitor: December 2020," https://www.kff.org/coronavirus-covid-19/report/kff-covid-19-vaccine-monitor-december-2020/.

Hardin, Garrett (1968), "The Tragedy of the Commons," *Science*, 162 (3859), 1243–48.

Hartman, Robert O., Nathan F. Dieckmann, Amber M. Sprenger, Bradley J. Stastny, and Kenneth G. DeMarree (2017), "Modeling Attitudes Toward Science: Development and Validation of the Credibility of Science Scale," *Basic and Applied Social Psychology*, 39 (6), 358–71.

Hayes, Andrew F. (2017), *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach.* US: Guilford Publications.

Hershey, John C., David A. Asch, Thi Thumasathit, Jacqueline Meszaros, and Victor V. Waters (1994), "The Roles of Altruism, Free Riding, and Bandwagoning in Vaccination Decisions," *Organizational Behavior and Human Decision Processes*, 59 (2), 177–87.

Huh, Young Eun, Joachim Vosgerau, and Carey K. Morewedge (2014), "Social Defaults: Observed Choices Become Choice Defaults," *Journal of Consumer Research*, 41 (3), 746–60.

Kahan, Dan M., Donald Braman, Paul Slovic, John Gastil, and Geoffrey Cohen (2009), "Cultural cognition of the risks and benefits of nanotechnology," *Nature Nanotechnology*, 4 (2), 87–90.

Kahneman, Daniel and Amos Tversky (1979), "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, 47 (2), 263-292.

Kennedy, Jonathan (2020), "Vaccine Hesitancy: A Growing Concern," *Pediatric Drugs*, 22 (2), 105–11.

Kreps, Sarah, Sandip Prasad, John S. Brownstein, Yulin Hswen, Brian T. Garibaldi, Baobao Zhang, and Douglas L. Kriner (2020), "Factors Associated With US Adults' Likelihood of Accepting COVID-19 Vaccination," *JAMA network open*, 3 (10), e2025594.

Kumar, Manoj, Devojit Kumar Sarma, Swasti Shubham, Manoj Kumawat, Vinod Verma, Praveen Balabaskaran Nina, Devraj JP, Santosh Kumar, Birbal Singh, and Rajnarayan R. Tiwari (2021), "Futuristic Non-antibiotic Therapies to Combat Antibiotic Resistance: A Review," *Frontiers in Microbiology*, 12, 609459.

Latkin, Carl A, Lauren Dayton, Grace Yi, Arianna Konstantopoulos, and Basmattee Boodram (2021), "Trust in a COVID-19 vaccine in the U.S.: A social-ecological perspective," *Social Science & Medicine*, 270, 113684.

Lee, Wan Ling, Zi Jing Lim, Li Yoong Tang, Nor Aziyan Yahya, Kasturi Dewi Varathan, and Salizar Mohamed Ludin (2022), "Patients' Technology Readiness and eHealth Literacy," *CIN: Computers, Informatics, Nursing*, 40 (4), 244–50.

Lehmann, Birthe A, Robert A C Ruiter, Gretchen Chapman, and Gerjo Kok (2014), "The intention to get vaccinated against influenza and actual vaccination uptake of Dutch healthcare personnel," *Vaccine*, 32 (51), 6986–91.

Litman, Leib, Jonathan Robinson, and Tzvi Abberbock (2017), "TurkPrime.com: A versatile crowdsourcing data acquisition platform for the behavioral sciences," *Behavior Research Methods*, 49 (2), 433–42.

For Review Version

Author Accepted Manuscript

Mahajan, Vijay, Eitan Muller, and Frank M. Bass (1990), "New Product Diffusion Models in Marketing: A Review and Directions for Research," *Journal of Marketing*, 54 (1), 1-26.

Mani, Zied and Inès Chouk (2018), "Consumer Resistance to Innovation in Services: Challenges and Barriers in the Internet of Things Era," *Journal of Product Innovation Management*, 35 (5), 780–807.

Moreau, Page and Stacy Wood (2019), "Introduction to the Special Issue on Consumer Response to Big Innovations," *Journal of the Association for Consumer Research*, 4 (3), 214–16.

Morewedge, Carey K. and Daniel Kahneman (2010), "Associative processes in intuitive judgment," *Trends in Cognitive Sciences*, 14 (10), 435–40.

Murphy, Jamie, Frédérique Vallières, Richard P. Bentall, Mark Shevlin, Orla McBride, Todd K. Hartman, Ryan McKay, Kate Bennett, Liam Mason, Jilly Gibson-Miller, Liat Levita, Anton P. Martinez, Thomas V. A. Stocks, Thanos Karatzias, and Philip Hyland (2021), "Psychological characteristics associated with COVID-19 vaccine hesitancy and resistance in Ireland and the United Kingdom," *Nature Communications*, 12 (1), 29.

Orme, Bryan K. (2010), *Getting started with conjoint analysis : strategies for product design and pricing research*. Research Publishers.

Ostrom, Elinor, Joanna Burger, Christopher B Field, Richard B Norgaard, and David Policansky (1999), "Revisiting the Commons: Local Lessons, Global Challenges," *Science*, 284 (5412), 278–82.

Parasuraman, A. and Charles L. Colby (2015), "An Updated and Streamlined Technology Readiness Index," *Journal of Service Research*, 18 (1), 59–74.

Parker, Andrew M., Raffaele Vardavas, Christopher S. Marcum, and Courtney A. Gidengil (2013), "Conscious Consideration of Herd Immunity in Influenza Vaccination Decisions," *American Journal of Preventive Medicine*, 45 (1), 118–21.

Prelec, Drazen (1998), "The Probability Weighting Function," *Econometrica*, 66 (3), 497-527.

Quiggin, John (1982), "A theory of anticipated utility," *Journal of Economic Behavior & Organization*, 3 (4), 323–43.

Ram, S and Jagdish N Sheth (1989), "Consumer Resistance to Innovations: The Marketing Problem and its solutions," *Journal of Consumer Marketing*, 6 (2), 5–14.

Riis, Jason, Joseph P. Simmons, and Geoffrey P. Goodwin (2008), "Preferences for Enhancement Pharmaceuticals: The Reluctance to Enhance Fundamental Traits," *Journal of Consumer Research*, 35 (3), 495–508.

Rogers, Everett M (1995), *Diffusion of Innovations.* Free Press.

Rothshild, Michael and Joseph E. Stiglitz (1970), "Increasing Risk: I. A Definition," *Journal of Economic Theory*, 2 (3), 225-243.

Rubin, Rita (2020), "Difficult to Determine Herd Immunity Threshold for COVID-19," *JAMA*, 324 (8), 732.

Savage, Leonard J. (1954), *The foundations of statistics*, John Wiley & Sons.

Savoia, Elena, Rachael Piltch-Loeb, Beth Goldberg, Cynthia Miller-Idriss, Brian Hughes, Alberto Montrond, Juliette Kayyem, and Marcia A. Testa (2021), "Predictors of COVID-19 Vaccine Hesitancy: Socio-Demographics, Co-Morbidity, and Past Experience of Racial Discrimination," *Vaccines*, 9 (7), 767.

Scovell, Mitchell D. (2022), "Explaining hydrogen energy technology acceptance: A critical review," *International Journal of Hydrogen Energy*, 47 (19), 10441–59.

Sedlmeier, Peter and Gerd Gigerenzer (1997), "Intuitions about sample size: the empirical law of large numbers," *Journal of Behavioral Decision Making*, 10 (1), 33–51.

Pre-Review Version

Author Accepted Manuscript

Shimp, Terence A., Eva M. Hyatt, and David J. Snyder (1991), "A Critical Appraisal of Demand Artifacts in Consumer Research," *Journal of Consumer Research*, 18 (3), 273-283.

Soane, Emma and Nik Chmiel (2005), "Are risk preferences consistent?," *Personality and Individual Differences*, 38 (8), 1781–91.

Societal Experts Action Network (2023), "Welcome to the Societal Experts Action Network (SEAN) COVID-19 Survey Archive" (accessed November 17, 2023), https://covid-19.parc.us.com

Sun, Christopher L. F., Eli Jaffe, and Retsef Levi (2022), "Increased emergency cardiovascular events among under-40 population in Israel during vaccine rollout and third COVID-19 wave," *Scientific Reports*, 12 (1), 6978.

Sun, Heshan (2013), "A Longitudinal Study of Herd Behavior in the Adoption and Continued Use of Technology," *MIS Quarterly*, 37 (4), 1013–41.

Tobin, James (1958), "Estimation of Relationships for Limited Dependent Variables," *Econometrica*, 26(1), 24-36.

Tversky, Amos and Daniel Kahneman (1992), "Advances in prospect theory: Cumulative representation of uncertainty," *Journal of Risk and Uncertainty*, 5, 297–323.

Vitiello, A, F Ferrara, V Troiano, and R La Porta (2021), "COVID-19 vaccines and decreased transmission of SARS-CoV-2," *Inflammopharmacology*, 29 (5), 1357–1360.

Wakker, Peter P. and Daniel Deneffe (1996), "Eliciting von Neumann-Morgenstern Utilities When Probabilities are Distorted or Unknown," *Management Science*, 42 (8), 1131–50.

Wakker, Peter P. (2010), *Prospect Theory*, Cambridge University Press.

Wang, Dengjun, Navid B. Saleh, Andrew Byro, Richard Zepp, Endalkachew Sahle-Demessie, Todd P. Luxton, Kay T. Ho, Robert M. Burgess, Markus Flury, Jason C. White, and Chunming Su (2022), "Nano-enabled pesticides for sustainable agriculture and global food security," *Nature Nanotechnology*, 17 (4), 347–60.

Watts, Duncan J. and Peter Sheridan Dodds (2007), "Influentials, Networks, and Public Opinion Formation," *Journal of Consumer Research*, 34 (4), 441–58.

Wilson, Steven Lloyd and Charles Wiysonge (2020), "Social media and vaccine hesitancy," *BMJ Global Health*, 5 (10), e004206.

Yu, Keming, Zudi Lu, and Julian Stander (2003), "Quantile Regression: Applications and Current Research Areas," *Journal of the Royal Statistical Society. Series D (The Statistician)*, 52 (3), 331–50.

Zhang, Wanqing, Pradeep K. Chintagunta, and Manohar U. Kalwani (2021), "Social Media, Influencers, and Adoption of an Eco-Friendly Product: Field Experiment Evidence from Rural China," *Journal of Marketing*, 85 (3), 10–27.

For Review Version

Author Accepted Manuscript

Web Appendix

Adoption of New Technology Vaccines

Laura Zimmermann, Assistant Professor of Marketing, IE Business School, Madrid, Spain, laura.zimmermann@ie.edu

Jeeva Somasundaram, Assistant Professor of Decision Sciences, IE Business School, Madrid, Spain, jeeva.somasundaram@ie.edu

Barsha Saha, Assistant Professor of Information Systems and Analytics, Jindal Global Business School, O.P. Jindal Global University & Indian Institute of Management Shillong, India, barsha.saha@jgu.edu.in

Peer Review Version

Table of Contents

These materials have been supplied by the authors to aid in the understanding of their paper. The AMA is sharing these materials at the request of the authors.

Author Accepted Manuscript

Web Appendix A: Mathematical Model

Proofs

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. An EU consumer takes up the vaccine if the expected utility of vaccinating is higher than the expected utility of not vaccinating, that is when

$$EU(Vaccinating) - EU(not\ Vaccinating) =$$

$$\beta q(1-p(1-E))u\left(h-c-\frac{\delta}{\beta q}\right) + (1-\beta)q(1-p(1-E))u\left(h-c+\frac{\delta}{((1-\beta)q)}\right)$$

$$+ (1-q)\big(1-p(1-E)\big)u(h) + (p(1-E))\beta q\, u\left(h-l-c-\frac{\delta}{\beta q}\right)$$

$$+ (p(1-E))((1-\beta)q)u\left(h-l-c+\frac{\delta}{((1-\beta)q)}\right) + (1-q)(p(1-E))u(h-l)$$

$$- pu(h-l) - (1-p)u(h)$$

The marginal utility of taking up a new (U_N) and a traditional technology vaccine (U_T) is given by

Peer Review Version

Author Accepted Manuscript

$$U_N - U_T = \beta q\big(1-p(1-E_N)\big)u\left(h-c-\frac{\delta_N}{\beta q}\right) + (1-\beta)q\big(1-p(1-E_N)\big)u\left(h-c+\frac{\delta_N}{(1-\beta)q}\right)$$
$$+ (1-q)\big(1-p(1-E_N)\big)u(h) + (p(1-E_N)\beta q)u\left(h-l-c-\frac{\delta_N}{\beta q}\right) + (p(1-E_N))(1$$
$$-\beta)q\,)u\left(h-l-c+\frac{\delta_N}{(1-\beta)q}\right) + (1-q)(p(1-E_N))u(h-l)] - [\beta q(1$$
$$-p(1-E_T))u\left(h-c-\frac{\delta_T}{\beta q}\right) + (1-\beta)q(1-p(1-E_T))u\left(h-c+\frac{\delta_T}{(1-\beta)q}\right)$$
$$+ (1-q)\big(1-p(1-E_T)\big)u(h) + (p(1-E_T))\beta q\,u\left(h-l-c-\frac{\delta_T}{\beta q}\right) + (p(1-E_T))(1$$
$$-\beta)q\,u\left(h-l-c+\frac{\delta_T}{(1-\beta)q}\right) + (1-q)(p(1-E_T))u(h-l)] + \epsilon$$

Replacing $E_N = E_T + k$, with $k \geq 0$, we get

$$\boldsymbol{U_N - U_T = (1-\beta)q\big(1-p(1-E_T)\big)\left[\left(u\left(h-c+\frac{\delta_N}{\beta q}\right) - u\left(h-c+\frac{\delta_T}{\beta q}\right)\right)\right]}$$
$$\boldsymbol{+\,\beta q[1-p(1-E_T)]\left[u\left(h-c-\frac{\delta_N}{\beta q}\right) - u\left(h-c-\frac{\delta_T}{\beta q}\right)\right]}$$
$$\boldsymbol{+\,(1-\beta)q[p(1-E_T)]\left[u\left(h-c-l+\frac{\delta_N}{\beta q}\right) - u\left(h-c-l+\frac{\delta_T}{\beta q}\right)\right]}$$
$$\boldsymbol{+\,\beta q[p(1-E_T)]\left[u\left(h-c-l-\frac{\delta_N}{\beta q}\right) - u\left(h-c-l-\frac{\delta_T}{\beta q}\right)\right]}$$
$$\left[\beta q(pk)u\left(h-c-\frac{\delta_N}{\beta q}\right) + (1-\beta)q(pk)u\left(h-c+\frac{\delta_N}{(1-\beta)q}\right) + (1-q)(1+pk)u(h)\right.$$
$$\left. + (-pk)\beta q\,u\left(h-l-c-\frac{\delta_N}{\beta q}\right)\right) - pk(1-\beta)q\,u\left(h-l-c+\frac{\delta_N}{(1-\beta)q}\right) + (1$$
$$-q)(-pk)u(h-l)] + \epsilon$$

(W.1.)

Peer Review Version

Author Accepted Manuscript

We ignore the effect of TR, i.e., ϵ for now as $E(\epsilon) = 0$, so on average it is not going to affect preferences. When $k = 0$, that is if $E_N = E_T$, then $U_N - U_T$ is reduced to the terms in bold.

$$U_N - U_T = \boldsymbol{(1-\beta)q(1-p(1-E_T))\left[\left(u\left(h-c+\frac{\delta_N}{\beta q}\right)-u\left(h-c+\frac{\delta_T}{\beta q}\right)\right)\right]}$$

$$\boldsymbol{+\beta q[1-p(1-E_T)]\left[u\left(h-c-\frac{\delta_N}{\beta q}\right)-u\left(h-c-\frac{\delta_T}{\beta q}\right)\right]}$$

$$\boldsymbol{+(1-\beta)q[p(1-E_T)]\left[u\left(h-c-l+\frac{\delta_N}{\beta q}\right)-u\left(h-c-l+\frac{\delta_T}{\beta q}\right)\right]}$$

$$\boldsymbol{+\beta q[p(1-E_T)]\left[u\left(h-c-l-\frac{\delta_N}{\beta q}\right)-u\left(h-c-l-\frac{\delta_T}{\beta q}\right)\right]}$$

We focus on the first two terms. The first term has a positive sign, and the second term has a negative sign. The side effects of the traditional technology vaccine are a mean preserving spread of the new technology vaccine. It is shown in (Rothshild and Stiglitz 1970) that an EU consumer with a concave utility function will avoid the mean preserving spread, therefore, $U_N - U_T < 0$. However, we show the proof step by step.

Consider the first two terms. Let us assume that the difference between the first two terms is greater than zero. In that case,

$$(1-\beta)q(1-p(1-E_T))\left[\left(u\left(h-c+\frac{\delta_N}{\beta q}\right)-u\left(h-c+\frac{\delta_T}{\beta q}\right)\right)\right]$$

$$+\beta q[1-p(1-E_T)]\left[u\left(h-c-\frac{\delta_N}{\beta q}\right)-u\left(h-c-\frac{\delta_T}{\beta q}\right)\right] > 0$$

Rearranging, we get $\frac{\left(u\left(h-c+\frac{\delta_N}{\beta q}\right)-u\left(h-c+\frac{\delta_T}{\beta q}\right)\right)}{u\left(h-c-\frac{\delta_T}{\beta q}\right)-u\left(h-c-\frac{\delta_N}{\beta q}\right)} > \frac{\beta}{(1-\beta)}$. Let us replace, $\delta_N = \delta_T + \Delta$, where $\Delta > 0$.

Author Accepted Manuscript

When the utility function is linear, then LHS = $\frac{\frac{\Delta}{1-\beta}}{\frac{\Delta}{\beta}} = \frac{\beta}{(1-\beta)} = RHS$ (the in-equality above is not satisfied). When the utility function is concave, $u\left(h-c+\frac{\delta_N}{\beta q}\right)-u\left(h-c+\frac{\delta_T}{\beta q}\right) < \frac{\Delta}{1-\beta}$. We represent it by $u\left(h-c+\frac{\delta_N}{\beta q}\right)-u\left(h-c+\frac{\delta_T}{\beta q}\right) = t \times \frac{\Delta}{1-\beta}$, where $t < 1$. On the other hand, similarly, $u\left(h-c-\frac{\delta_T}{\beta q}\right)-u\left(h-c-\frac{\delta_N}{\beta q}\right) = t' \times \frac{\Delta}{\beta}$. Note that $1 > t' > t > 0$. Therefore, when the utility function is concave,

$$\frac{\left(u\left(h-c+\frac{\delta_N}{\beta q}\right)-u\left(h-c+\frac{\delta_T}{\beta q}\right)\right)}{u\left(h-c-\frac{\delta_T}{\beta q}\right)-u\left(h-c-\frac{\delta_N}{\beta q}\right)} < \frac{\beta}{(1-\beta)}$$

This implies $(1-\beta)q(1-p(1-E_T))\left[\left(u\left(h-c+\frac{\delta_N}{\beta q}\right)-u\left(h-c+\frac{\delta_T}{\beta q}\right)\right)\right]+\beta q[1-p(1-E_T)]\left[u\left(h-c-\frac{\delta_N}{\beta q}\right)-u\left(h-c-\frac{\delta_T}{\beta q}\right)\right] < 0$. Similarly, we can show that the difference between the third and the fourth term is also less than zero. Therefore, $U_N - U_T < 0$. When we incorporate ϵ into the equation, there could be considerable heterogeneity in $U_N - U_T$, but still $U_N - U_T < 0$ on average as $E(\epsilon) = 0$.

In Eq. (W.1.), the non-bolded terms and therefore $U_N - U_T$ increase with k. When k is larger, $U_N - U_T$ can become greater than zero. As $U_N - U_T$ is continuous, we can find a $k > 0$ but close to zero, such that $U_N - U_T < 0$. Thus, Lemma 1 is proven.

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* $k' \geq k$;

Peer Review Version

Author Accepted Manuscript

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

Proof. We calculate the rank dependent utility (RDU) value by ordering the outcomes and then applying probability weights based on the rank dependence rule (Tversky and Kahneman 1992). A RDU consumer takes up the vaccine if the RDU value of vaccinating is higher than the RDU value of not vaccinating, that is when

$$
\begin{aligned}
&U(Vaccinating) - U(not\ Vaccinating) \\
&\quad = w\Big(\big(1-p(1-E)\big)(1-q)\Big)\,u(h) \\
&\quad + \Big(w\Big(\big(1-p(1-E)\big)(1-\beta q)\Big) - w\Big(\big(1-p(1-E)\big)(1-q)\big)\Big)\,u\left(h-c+\frac{\delta}{(1-\beta)q}\right) \\
&\quad + \Big(w\big(1-p(1-E)\big) - w\Big(\big(1-p(1-E)\big)(1-\beta q)\big)\Big)\,u\left(h-c-\frac{\delta}{\beta q}\right) \\
&\quad + \big(w\Big(\big(1-p(1-E)q\big) - w\big(1-p(1-E)\big)\Big)\,u(h-l) + \big(w\big((1-p(1-E)\beta q\big) \\
&\quad - w\big((1-p(1-E)q\big)\big)u\left(h-l-c+\frac{\delta}{(1-\beta)q}\right) \\
&\quad + \Big(1-w\big((1-p(1-E)\beta q\big)\big)\Big)\,u\left(h-l-c-\frac{\delta}{\beta q}\right) - w(1-p)u(h) \\
&\quad - \big(1-w(1-p)\big)u(h-l)
\end{aligned}
$$

Peer Review Version

Author Accepted Manuscript

$$
\begin{aligned}
U_N - U_T = {} & w\Big(\big(1-p(1-E_N)\big)(1-q)\Big)\,u(h) \\
& + \Big(w\Big(\big(1-p(1-E_N)\big)(1-\beta q)\Big) - w\Big(\big(1-p(1-E_N)\big)(1-q)\Big)\Big)\,u\Big(h-c \\
& + \frac{\delta_N}{(1-\beta)\mathrm{q}}\Big) \\
& + \Big(w\big(1-p(1-E_N)\big) - w\Big(\big(1-p(1-E_N)\big)(1-\beta q)\Big)\Big)\,u\Big(h-c-\frac{\delta_N}{\beta\mathrm{q}}\Big) \\
& + \Big(w\Big(\big(1-p(1-E_N)q\big) - w\big(1-p(1-E_N)\big)\Big)\,u(h-l) + \big(w\big((1-p(1-E_N)\beta q\big) \\
& - w\big(\big(1-p(1-E_N)q\big)\big)u\Big(h-l-c+\frac{\delta_N}{(1-\beta)q}\Big) \\
& + \Big(1-w\big(\big(1-p(1-E_N)\beta q\big)\big)\Big)\,u\Big(h-l-c-\frac{\delta_N}{\beta q}\Big) \\
& - w\Big(\big(1-p(1-E_T)\big)(1-q)\Big)\,u(h) \\
& - \Big(w\Big(\big(1-p(1-E_T)\big)(1-\beta q)\Big) - w\Big(\big(1-p(1-E_T)\big)(1-q)\Big)\Big)\,u\Big(h-c \\
& + \frac{\delta_T}{(1-\beta)\mathrm{q}}\Big) \\
& - \Big(w\big(1-p(1-E_T)\big) - w\Big(\big(1-p(1-E_T)\big)(1-\beta q)\Big)\Big)\,u\Big(h-c-\frac{\delta_T}{(\beta)\mathrm{q}}\Big) \\
& - \big(w\Big(\big(1-p(1-E_T)q\big) - w\big(1-p(1-E_T)\big)\Big)\,u(h-l) - \big(w\big((1-p(1-E_T)\beta q\big) \\
& - w\big(\big(1-p(1-E_T)q\big)\big)u\Big(h-l-c+\frac{\delta_T}{(1-\beta)q}\Big) \\
& - \Big(1-w\big(\big(1-p(1-E_T)\beta q\big)\big)\Big)\,u\Big(h-l-c-\frac{\delta_T}{\beta q}\Big) + \epsilon
\end{aligned}
$$

Peer Review Version

Author Accepted Manuscript

Replacing $E_N = E_T + k'$, we get

$$
\begin{aligned}
U_N - U_T = {} & w\Big(\big(1-p(1-E_T-k')\big)(1-q)\Big)\,u(h) \\
& + \Big(w\Big(\big(1-p(1-E_T-k')\big)(1-\beta q)\Big) - w\Big(\big(1-p(1-E_T-k')\big)(1-q)\Big)\Big)\,u\Big(h \\
& - c + \frac{\delta_N}{(1-\beta)\mathrm{q}}\Big) \\
& + \Big(w\big(1-p(1-E_T-k')\big) - w\Big(\big(1-p(1-E_T-k')\big)(1-\beta q)\Big)\Big)\,u\Big(h-c-\frac{\delta_N}{\beta \mathrm{q}}\Big) \\
& + \big(w\Big(\big(1-p\big(1-E_T-k^{'}\big)q\big) - w\Big(1-p\big(1-E_T-k^{'}\big)\Big)\Big)\,u(h-l) \\
& + \big(w\big(\big(1-p\big(1-E_T-k^{'}\big)\beta q\big) \\
& - w\Big(\big(1-p\big(1-E_T-k^{'}\big)q\big)\Big)\,u\Big(h-l-c+\frac{\delta_N}{(1-\beta)q}\Big) \\
& + \Big(1-w\Big(\big(1-p\big(1-E_T-k^{'}\big)\beta q\big)\Big)\Big)\,u\Big(h-l-c-\frac{\delta_N}{\beta q}\Big) \\
& - w\Big(\big(1-p(1-E_T)\big)(1-q)\Big)\,u(h) \\
& - \Big(w\Big(\big(1-p(1-E_T)\big)(1-\beta q)\Big) - w\Big(\big(1-p(1-E_T)\big)(1-q)\Big)\Big)\,u\Big(h-c \\
& + \frac{\delta_T}{(1-\beta)\mathrm{q}}\Big) \\
& - \Big(w\big(1-p(1-E_T)\big) - w\Big(\big(1-p(1-E_T)\big)(1-\beta q)\Big)\Big)\,u\Big(h-c-\frac{\delta_T}{(\beta)\mathrm{q}}\Big) \\
& - \big(w\Big(\big(1-p(1-E_T)q\big) - w\big(1-p(1-E_T)\big)\Big)\,u(h-l) - \big(w\big(\big(1-p(1-E_T)\beta q\big) \\
& - w\big(\big(1-p(1-E_T)q\big)\big)u\Big(h-l-c+\frac{\delta_T}{(1-\beta)q}\Big) \\
& - \Big(1-w\big(\big(1-p(1-E_T)\beta q\big)\big)\Big)\,u\Big(h-l-c-\frac{\delta_T}{\beta q}\Big) + \epsilon
\end{aligned}
$$

(W.2.)

For Peer Review Version

Author Accepted Manuscript

When $k' = 0$, that is if $E_N = E_T$ (we also ignore ϵ for now as, on average, $E(\epsilon) = 0$), we get

$$U_N - U_T = \Big(w\Big(\big(1-p(1-E_T)\big)(1-\beta q)\Big) - w\Big(\big(1-p(1-E_T)\big)(1-q)\Big)\Big)\Big(u\Big(h-c+\frac{\delta_N}{(1-\beta)q}\Big) - u\Big(h-c+\frac{\delta_T}{(1-\beta)q}\Big)\Big)$$
$$+\Big(w\big(1-p(1-E_T)\big) - w\Big(\big(1-p(1-E_T)\big)(1-\beta q)\Big)\Big)\Big(u\Big(h-c-\frac{\delta_N}{\beta q}\Big) - u\Big(h-c-\frac{\delta_T}{\beta q}\Big)\Big) + \big(w\big((1-p(1-E_T)\beta q\big)$$
$$- w\big((1-p(1-E_T)q\big)\Big)\Big(u\Big(h-l-c+\frac{\delta_N}{(1-\beta)q}\Big) - u\Big(h-l-c+\frac{\delta_T}{(1-\beta)q}\Big)\Big)$$
$$+\Big(1-w\big((1-p(1-E_T)\beta q\big)\big)\Big)\Big(u\Big(h-l-c-\frac{\delta_N}{\beta q}\Big) - u\Big(h-l-c-\frac{\delta_T}{\beta q}\Big)\Big)$$

For an inverse-s weighting function, due to convexity of the probability weighting function for $p > p^*$, $\Big(w\Big(\big(1-p(1-E_T)\big)(1-\beta q)\Big) - w\Big(\big(1-p(1-E_T)\big)(1-q)\Big)\Big) < w\big(1-p(1-E_T)\big) - w\Big(\big(1-p(1-E_T)\big)(1-\beta q)\Big)$ (the weight of the first term is lower than of the second term) and $\big(w\big((1-p(1-E_T)\beta q\big) - w\big((1-p(1-E_T)q\big)\big) < \Big(1-w\big((1-p(1-E_T)\beta q\big)\big)\Big)$ (the weight of the third term is lower than of the fourth term), and u is concave and therefore $u\Big(h-c-l-\frac{\delta_T}{\beta q}\Big) - u\Big(h-c-l-\frac{\delta_N}{\beta q}\Big) > u\Big(h-c-l+\frac{\delta_N}{(1-\beta)q}\Big) - u\Big(h-c-l+\frac{\delta_T}{(1-\beta)q}\Big)$ and $\Big(u\Big(h-c-\frac{\delta_T}{\beta q}\Big) - u\Big(h-c-\frac{\delta_N}{\beta q}\Big)\Big) > u\Big(h-c+\frac{\delta_N}{(1-\beta)q}\Big) - u\Big(h-c+\frac{\delta_T}{(1-\beta)q}\Big)$. Therefore, $U_N - U_T < 0$.

Peer Review Version

Author Accepted Manuscript

$U_N - U_T$ becomes more negative as w exhibits more inverse-s weighting (or for lower α), that is higher overweighting for $p < p^*$ and higher underweighting for $p > p^*$. Note that as in the previous case ϵ_T might affect heterogeneity but still on average $U_N - U_T < 0$.

In Eq. (W.2.) $U_N - U_T$ increases with k'. When k' > 0, as $U_N - U_T$ is continuous, we can find a k' close to zero, such that $U_N - U_T < 0$. As w is concave for $p < p^*$, the effect of reducing the probability of infection by increasing k' is not as strong as the linear case (i.e., Lemma 1), therefore k' > k. In other words, the consumer prefers the traditional technology vaccine over the new technology vaccine for a higher $E_N - E_T$, when the weighting function is more concave (resp., more convex) for $p < p^*$ (resp., $p > p^*$).

Proposition: *When the herd immunity effect is small, with an increase in the 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 probabilities p < p, there will be a greater increase in the uptake of a new relative to a traditional technology vaccine.*

Proof. Incorporating the dependencies of $p, v, and\ \delta$ on θ, we get the following. A risk-averse EU consumer takes up the vaccine after seeing the population vaccination rate when

Peer Review Version

Author Accepted Manuscript

$$U = \beta q\big(1 - p(\theta)(1 - E)\big)u\left(h - c - \frac{\delta(\theta)}{\beta q}\right) + (1 - \beta)q\big(1 - p(\theta)(1 - E)\big)u\left(h - c + \frac{\delta(\theta)}{(1-\beta)q}\right) + (1 - q)\big(1 - p(\theta)(1 - E)\big)u(h) + (p(\theta)(1 - E))\beta q\, u\left(h - l - c - \frac{\delta(\theta)}{\beta q}\right) + (p(\theta)(1 - E))(1 - \beta)q\, u\left(h - l - c + \frac{\delta(\theta)}{(1-\beta)q}\right) + (1 - q)(p(\theta)(1 - E))u(h - l) - p(\theta)u(h - l) - (1 - p(\theta))u(h) + \bar{u}(\theta) + \epsilon$$

$$U_N - U_T = (1 - \beta)q\big(1 - p(\theta)(1 - E_T)\big)\left[\left(u\left(h - c + \frac{\delta_N}{\beta q}\right) - u\left(h - c + \frac{\delta_T}{\beta q}\right)\right)\right] + \beta q[1 - p(\theta)(1 - E_T)]\left[u\left(h - c - \frac{\delta_N}{\beta q}\right) - u\left(h - c - \frac{\delta_T}{\beta q}\right)\right] + (1 - \beta)q[p(\theta)(1 - E_T)]\left[u\left(h - c - l + \frac{\delta_N}{\beta q}\right) - u\left(h - c - l + \frac{\delta_T}{\beta q}\right)\right] + \beta q[p(\theta)(1 - E_T)]\left[u\left(h - c - l - \frac{\delta_N}{\beta q}\right) - u\left(h - c - l - \frac{\delta_T}{\beta q}\right)\right] + \left[\boldsymbol{\beta q(p(\theta)k)u\left(h - c - \frac{\delta_N(\theta)}{\beta q}\right)} + \boldsymbol{(1 - \beta)q(p(\theta)k)u\left(h - c + \frac{\delta_N(\theta)}{(1-\beta)q}\right)} + \boldsymbol{(1 - q)(1 + p(\theta)k)u(h)} + \boldsymbol{(-p(\theta)k)\beta q\, u\left(h - l - c - \frac{\delta_N(\theta)}{\beta q}\right)} + \boldsymbol{(-p(\theta)k)}\right)\boldsymbol{(1 - \beta)q\ u\left(h - l - c + \frac{\delta_N(\theta)}{(1-\beta)q}\right)} + \boldsymbol{(1 - q)(-p(\theta)k)u(h - l)}] + \epsilon$$

(W.3.)

Case 1: We analyze the case when there is no herd immunity effect i.e., we equate $p(\theta) = p$, and we get

$$(1 - \beta)q\big(1 - p(\theta)(1 - E_T)\big)\left[\left(u\left(h - c + \frac{\delta_N}{\beta q}\right) - u\left(h - c + \frac{\delta_T}{\beta q}\right)\right)\right] + \beta q[1 - p(\theta)(1 - E_T)]\left[u\left(h - c - \frac{\delta_N}{\beta q}\right) - u\left(h - c - \frac{\delta_T}{\beta q}\right)\right] + (1 - \beta)q[p(\theta)(1 - E_T)]\left[u\left(h - c - l + \frac{\delta_N}{\beta q}\right) - u\left(h - c - l + \frac{\delta_T}{\beta q}\right)\right] + \beta q[p(\theta)(1 - E_T)]\left[u\left(h - c - l - \frac{\delta_N}{\beta q}\right) - u\left(h - c - l - \frac{\delta_T}{\beta q}\right)\right] + \left[\boldsymbol{\beta q(pk)u\left(h - c - \frac{\delta_N(\theta)}{\beta q}\right)} + \boldsymbol{(1 - \beta)q(pk)u\left(h - c + \frac{\delta_N(\theta)}{(1-\beta)q}\right)} + \boldsymbol{(1 - q)(1 + pk)u(h)} + \boldsymbol{(-pk)\beta q\, u\left(h - l - c - \frac{\delta_N(\theta)}{\beta q}\right)} + \boldsymbol{(-pk)}\right)\boldsymbol{(1 - \beta)q\ u\left(h - l - c + \frac{\delta_N(\theta)}{(1-\beta)q}\right)} + \boldsymbol{(1 - q)(-pk)u(h - l)}] + \epsilon$$

(W.4.)

Peer Review Version

Author Accepted Manuscript

We first assume $E_N = E_T$ and $k = 0$. We differentiate the above with respect to θ, and get

$\frac{\partial(U_N - U_T)}{\partial\theta} = \beta q(1 - p(1 - E_T))\left[\left(u'\left(h - c - \frac{\delta_N(1-\theta)}{\beta q}\right) \times \frac{\delta_N}{\beta q} - \frac{\delta_T}{\beta q} \times u'\left(h - c - \frac{\delta_T(1-\theta)}{\beta q}\right) - u'\left(h - c + \frac{\delta_N(1-\theta)}{(1-\beta)q}\right) \times \frac{\delta_N}{(1-\beta)q}\right) + \frac{\delta_T}{(1-\beta)q} \times u'\left(h - c + \frac{\delta_T(1-\theta)}{(1-\beta)q}\right)\right] + \beta q[p(1 - E_T)]\left[\left(u'\left(h - l - c - \frac{\delta_N(1-\theta)}{\beta q}\right) \times \frac{\delta_N}{\beta q} - \frac{\delta_T}{\beta q} \times u'\left(h - l - c - \frac{\delta_T(1-\theta)}{\beta q}\right) - u'\left(h - l - c + \frac{\delta_N(1-\theta)}{(1-\beta)q}\right) \times \frac{\delta_N}{(1-\beta)q}\right) + \frac{\delta_T}{(1-\beta)q} \times u'\big(h - l - c + \delta_T(1-\theta)\big)/(1-\beta)q\ )\right]$

For utility functions that have $u''' > 0$ (prudence; Eeckhoudt and Gollier 2005) such as the power or exponential utility function, we see that $\left[\left(u'\left(h - c - \frac{\delta_N(1-\theta)}{\beta q}\right) \times \frac{\delta_N}{\beta q} - \frac{\delta_T}{\beta q} \times u'\left(h - c - \frac{\delta_T(1-\theta)}{\beta q}\right) - u'\left(h - c + \frac{\delta_N(1-\theta)}{(1-\beta)q}\right) \times \frac{\delta_N}{(1-\beta)q}\right) + \frac{\delta_T}{(1-\beta)q} \times u'\left(h - c + \frac{\delta_T(1-\theta)}{(1-\beta)q}\right)\right] > 0$ and $\left[\left(u'\left(h - l - c - \frac{\delta_N(1-\theta)}{\beta q}\right) \times \delta_N - \delta_T \times u'\left(h - l - c - \frac{\delta_T(1-\theta)}{\beta q}\right) - u'\left(h - l - c + \frac{\delta_N(1-\theta)}{(1-\beta)q}\right) \times \delta_N\right) + \delta_T \times u'\left(h - l - c + \frac{\delta_T(1-\theta)}{(1-\beta)q}\right)\right] > 0$. Therefore, $U_N - U_T$ increases with θ.

Suppose $E_N - E_T = k$ and $k > 0$. Differentiating Eq. (W.4.), we know that $\frac{\partial(U_N - U_T)}{\partial\theta} > 0$ for the non-bolded terms (i.e., when k = 0). Differentiating only the bolded terms in Eq. (W.4.) with regard to θ, we get

$$pk\delta_N\left[u'\left(h - c - \frac{\delta_N(1-\theta)}{\beta q}\right) - u'\left(h - l - c - \frac{\delta_N(1-\theta)}{\beta q}\right)\right] + pk\delta_N\left[u'\left(h - l - c + \frac{\delta_N(1-\theta)}{(1-\beta)q}\right) - u'\left(h - c + \frac{\delta_N(1-\theta)}{(1-\beta)q}\right)\right]$$

The first term in the expression above $\left(u'\left(h - c - \frac{\delta_N(1-\theta)}{\beta q}\right) - u'\left(h - l - c - \frac{\delta_N(1-\theta)}{\beta q}\right)\right.$ is negative and the second term in the expression $\left.\left(u'\left(h - l - c + \frac{\delta_N(1-\theta)}{(1-\beta)q}\right) - u'\left(h - c + \frac{\delta_N(1-\theta)}{(1-\beta)q}\right)\right)\right.$ is positive. As $\beta < 0.5$ and as $u''' > 0$, the above expression is positive. Therefore, $\frac{\partial(U_N - U_T)}{\partial\theta} > 0$.

Peer Review Version

Author Accepted Manuscript

In other words, there is a stronger increase in uptake of the new vis-à-vis traditional technology vaccine as the population vaccination rate increases. The increase in uptake is higher when the new technology vaccine has a higher efficacy.

Case 2: We allow for a herd immunity effect, that is we allow $p(\theta)$ to decrease with θ.

We differentiate $\frac{\partial(U_N-U_T)}{\partial\theta}$ by first assuming $E_N = E_T$ and k = 0. We get

$$\frac{\partial(U_N-U_T)}{\partial\theta} = \beta q\left(1-p(\theta)(1-E_T)\right)\left[\left(u'\left(h-c-\frac{\delta_N(1-\theta)}{\beta q}\right)\times\frac{\delta_N}{\beta q}-\frac{\delta_T}{\beta q}\times u'\left(h-c-\frac{\delta_T(1-\theta)}{\beta q}\right)-\right.\right.$$

$$\left.u'\left(h-c+\frac{\delta_N(1-\theta)}{(1-\beta)q}\right)\times\frac{\delta_N}{(1-\beta)q}\right)+\frac{\delta_T}{(1-\beta)q}\times u'\left(h-c+\frac{\delta_T(1-\theta)}{(1-\beta)q}\right)\Big] + (1-\beta)q[p(\theta)(1-E_T)]\left[\left(u'\left(h-l-\right.\right.\right.$$

$$\left.\left.c-\frac{\delta_N(1-\theta)}{\beta q}\right)\times\frac{\delta_N}{\beta q}-\frac{\delta_T}{\beta q}\times u'\left(h-l-c-\frac{\delta_T(1-\theta)}{\beta q}\right)-u'\left(h-l-c+\frac{\delta_N(1-\theta)}{(1-\beta)q}\right)\times\frac{\delta_N}{(1-\beta)q}\right)+$$

$$\left.\frac{\delta_T}{(1-\beta)q}\times u'(h-l-c+\delta_T(1-\theta)/(1-\beta)q\,)\right]+\left[\left(\boldsymbol{u\left(h-c-l-\frac{\delta_N(\theta)}{\beta q}\right)-u\left(h-c-l-\frac{\delta_T(\theta)}{\beta q}\right)}\right)+\right.$$

$$\left.\boldsymbol{u\left(h-c-l+\frac{\delta_N(\theta)}{(1-\beta)q}\right)-u(h-c-l+\delta_T(\theta)/(1-\beta)q)}\right]\boldsymbol{\beta q}[\boldsymbol{p'(\theta)(1-E_T)}]-\boldsymbol{(1-\beta)qp'(\theta)(1-}$$

$$\boldsymbol{E_T)}\left[\left(\boldsymbol{u\left(h-c-\frac{\delta_N(\theta)}{\beta q}\right)-u\left(h-c-\frac{\delta_T(\theta)}{\beta q}\right)}\right)+\boldsymbol{u\left(h-c+\frac{\delta_N(\theta)}{(1-\beta)q}\right)-u\left(h-c+\frac{\delta_T(\theta)}{(1-\beta)q}\right)}\right]$$

(W.5.)

The first two terms in the above equation (non-bolded) correspond to $\frac{\partial(U_N-U_T)}{\partial\theta}$ when $p(\theta) = p$ (case 1). Therefore, $\frac{\partial(U_N-U_T)}{\partial\theta} > 0$. In the bolded terms, the last term is negative. However, as we know that $u''' > 0$ and $\beta < 0.5$, $\left[\left(u\left(h-c-l-\frac{\delta_N(\theta)}{\beta q}\right)-u\left(h-c-l-\frac{\delta_T(\theta)}{\beta q}\right)\right)+u\left(h-c-l+\frac{\delta_N(\theta)}{(1-\beta)q}\right)-\right.$

$$\left.u\left(h-c-l+\frac{\delta_T(\theta)}{(1-\beta)q}\right)\right] > \left[\left(u\left(h-c-\frac{\delta_N(\theta)}{\beta q}\right)-u\left(h-c-\frac{\delta_T(\theta)}{\beta q}\right)\right)+u\left(h-c+\frac{\delta_N(\theta)}{(1-\beta)q}\right)-u\left(h-c+\right.\right.$$

$$\left.\left.\frac{\delta_T(\theta)}{(1-\beta)q}\right)\right].$$

Peer Review Version

Author Accepted Manuscript

Therefore, the expression above is always increasing. In other words, the herd immunity effect does not affect the marginal utility of choosing between the new and traditional technology vaccine when both have the same efficacy.

We now consider the case when $E_N - E_T = k$, where $k > 0$. We know that $\frac{\partial(U_N - U_T)}{\partial\theta} > 0$ for the non-bolded terms in Eq. (W.3) as shown above. Differentiating only the bolded terms in Eq. (W.3.) with regard to θ, we get

$$\beta q p(\theta) k \delta_N \left[u'\left(h - c - \frac{\delta_N(1-\theta)}{\beta q}\right) - u'\left(h - l - c - \frac{\delta_N(1-\theta)}{\beta q}\right)\right] + (1-\beta)q$$

$$p(\theta) k \delta_N \left[u'\left(h - l - c + \frac{\delta_N(1-\theta)}{(1-\beta)q}\right) - u'\left(h - c + \frac{\delta_N(1-\theta)}{(1-\beta)q}\right)\right]$$

$$+ \quad (1-q)p'(\theta)k(u(h) - u(h-l)) + (1-\beta)qp'(\theta)\left[u\left(h - c - \frac{\delta_N(1-\theta)}{\beta q}\right) - u\left(h - l - c - \frac{\delta_N(1-\theta)}{\beta q}\right)\right] + (1-\beta)qp'(\theta)\left[u\left(h - c + \frac{\delta_N(1-\theta)}{(1-\beta)q}\right) - u\left(h - l - c + \frac{\delta_N(1-\theta)}{(1-\beta)q}\right)\right]$$

In the above expression, the first two terms are positive, but the last three terms $(1-q)p'(\theta)k(u(h) - u(h-l)) + (1-\beta)qp'(\theta)\left[u\left(h - c - \frac{\delta_N(1-\theta)}{\beta q}\right) - u\left(h - l - c - \frac{\delta_N(1-\theta)}{\beta q}\right)\right] + (1-\beta)qp'(\theta)\left[u\left(h - c + \frac{\delta_N(1-\theta)}{(1-\beta)q}\right) - u\left(h - l - c + \frac{\delta_N(1-\theta)}{(1-\beta)q}\right)\right]$ are negative.

However, Eq. (W.5.) is positive, hence $\frac{\partial(U_N - U_T)}{\partial\theta} > 0$. In other words, if the herd immunity effect is strong and when $E_N > E_T$, there could be a negative effect of herd immunity on the reduction of new technology aversion. However, it is less likely to happen. Thus, the proposition is proven for an EU consumer.

Peer Review Version

Author Accepted Manuscript

A RDU consumer takes up the vaccine after seeing the population vaccination rate when:

Case 1': We analyze the case when there is no herd immunity effect i.e., we equate $p(\theta) = p$, and we get

Assuming $E_N = E_T$,

$$U_N - U_T = \left(w\left((1-p(1-E_T))(1-\beta q)\right) - w\left((1-p(1-E_T))(1-q)\right)\right)\left(u\left(h-c+\frac{\delta_N(1-\theta)}{(1-\beta)\mathrm{q}}\right)\right.$$
$$\left. - u\left(h-c+\frac{\delta_T(1-\theta)}{(1-\beta)\mathrm{q}}\right)\right)$$
$$+\left(w(1-p(1-E_T)) - w\left((1-p(1-E_T))(1-\beta q)\right)\right)\left(u\left(h-c-\frac{\delta_N(1-\theta)}{\beta\mathrm{q}}\right)\right.$$
$$\left. - u\left(h-c-\frac{\delta_T(1-\theta)}{\beta\mathrm{q}}\right)\right) + (w((1-p(1-E_T)\beta q)$$
$$- w((1-p(1-E_T)q))\left(u\left(h-l-c+\frac{\delta_N(1-\theta)}{(1-\beta)\mathrm{q}}\right) - u\left(h-l-c+\frac{\delta_T(1-\theta)}{(1-\beta)\mathrm{q}}\right)\right)$$
$$+\left(1-w((1-p(1-E_T)\beta q))\right)\left(u\left(h-l-c-\frac{\delta_N(1-\theta)}{\beta q}\right)\right.$$
$$\left. - u\left(h-l-c-\frac{\delta_T(1-\theta)}{\beta q}\right)\right)$$

Note that w is concave for the probabilities for $p < p^*$ and convex for $p > p^*$ considered.

Peer Review Version

Author Accepted Manuscript

$$\frac{\partial(U_N - U_T)}{\partial\theta} = -\Big(w\Big((1-p(1-E_T))(1-\beta q)\Big)$$

$$- w\Big((1-p(1-E_T))(1-q)\Big)\Big)\Big[-\frac{\delta_N}{(1-\beta)q}u'\Big(h-c+\frac{\delta_N(1-\theta)}{(1-\beta)q}\Big)$$

$$+\frac{\delta_T}{(1-\beta)q}u'\Big(h-c+\frac{\delta_T(1-\theta)}{(1-\beta)q}\Big)\Big]$$

$$-\Big(w(1-p(1-E_T)) - w\Big((1-p(1-E_T))(1-\beta q)\Big)\Big)\Big[-\delta_N u'\Big(h-c-\frac{\delta_N(1-\theta)}{\beta q}\Big)$$

$$+\delta_T u'\Big(h-c-\frac{\delta_T(1-\theta)}{\beta q}\Big)\Big] - (w((1-p(1-E_T)\beta q)$$

$$- w\big((1-p(1-E_T)q\big)\big(-\delta_N u'\big(\Big(h-l-c+\frac{\delta_N(1-\theta)}{(1-\beta)q}\Big)$$

$$+\delta_T u'\Big(h-l-c+\frac{\delta_T(1-\theta)}{(1-\beta)q}\Big)\big) - (1$$

$$- w\big((1-p(1-E_T)\beta q)\big)\big(\delta_N u'\Big(h-l-c-\frac{\delta_N(1-\theta)}{\beta q}\Big)$$

$$-\delta_T u'\Big(h-l-c-\frac{\delta_T(1-\theta)}{\beta q}\Big)\big)$$

(W.6.)

For a linear weighting function w, the case is identical to the EU case. Therefore, $\frac{\partial(U_N-U_T)}{\partial\theta} > 0$. The fourth term above is positive and is weighted more under inverse-s weighting compared to the third term which is negative. Similarly, the second term, which is positive, is weighted more under inverse-s weighting compared to the first term which is negative. Due to prudence of the utility function (u''' > 0), the fourth term minus the third term is positive and the second term minus the first term is also positive. Therefore, $\frac{\partial(U_N-U_T)}{\partial\theta} > 0$ and it is larger under an inverse-s weighting function than a linear weighting function. Therefore, consumers with an inverse-s weighting function respond more strongly to the social proof nudge.

Author Accepted Manuscript

Now we are assuming $E_N - E_T = k$, where $k > 0$. This lowers the probability of infection under the new technology vaccine. For the linear case, we showed that when $E_N > E_T$, there is a stronger increase in adoption of the new vis-à-vis traditional technology vaccine, when $k > 0$ (see case 1 of the proof). Since we have an inverse-S weighting function, the effect of k is stronger in Eq. (W.6.) for the fourth term than the third term and stronger for the second than the first term. As the fourth and second terms are positive, the inverse-S weighting function leads to stronger increase in $U_N - U_T$ with respect to θ.

Case 2': We allow for a herd immunity effect, that is we allow $p(\theta)$ to decrease with θ. When we differentiate $\frac{\partial(U_N - U_T)}{\partial\theta}$, in addition to the terms we have in Case 1', we first consider the case when $E_N = E_T$.

$$
\begin{aligned}
&-[u(h-l-c-\delta_N(\theta)) - u(h-l-c-\delta_T(\theta))]\frac{\partial w\left((1-w((1-p(\theta)(1-E_T)\beta q))\right)}{\partial\theta} \\
&\quad - [u(h-l-c+\delta_N(\theta)) - u(h-l-c+\delta_T(\theta))]\frac{\partial}{\partial\theta}\Big(w((1-p(\theta)(1-E_T)\beta q) \\
&\quad - w\big((1-p(\theta)(1-E_T)q)\big)\Big) \\
&\quad - [u(h-c-\delta_N(\theta)) \\
&\quad - u(h-c-\delta_T(\theta))]\frac{\partial}{\partial\theta}\Big(\Big(w\big(1-p(\theta)(1-E_T)\big) \\
&\quad - w\Big(\big(1-p(\theta)(1-E_T)\big)(1-\beta q)\Big)\Big)\Big) \\
&\quad - [u(h-c+\delta_N(\theta)) - u(h-c+\delta_T(\theta))]\frac{\partial}{\partial\theta}\Big(w\Big(\big(1-p(\theta)(1-E_T)\big)(1-\beta q)\Big) \\
&\quad - w\Big(\big(1-p(\theta)(1-E_T)\big)(1-q)\Big)\Big)
\end{aligned}
$$

Author Accepted Manuscript

In the above equation, the first and third term are positive but second and fourth term are negative. Due to concavity of the weighting function, as $p(\theta)$ is decreasing, the first term is expected to increase more than the second term (due to convexity of the weighting function for $p > p^*$, the first term is expected to decrease more than the weighting function in the second term). Similarly, the third term is expected to increase more than the fourth term. Due to the above and Case 1', $\frac{\partial(U_N - U_T)}{\partial\theta} > 0$. However, when $E_N - E_T = k$, where $k > 0$, we know from Case 2 that if the herd immunity effect is very large, then $U_N - U_T$ might decrease with θ. But it is less likely to happen. Due to the inverse-S weighting function, this decrease will be smaller. Thus, proposition 1 is proven.

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.*

Proof. To study the effect of a herd immunity threshold, for simplicity, without loss of generality, we study the case when there is utility of conforming that is when $\bar{u}(\theta) \to 0$. As we assume the herd behavior effects are similar across the new and traditional technology vaccine, the $\bar{u}(\theta)$ term will not affect our results.

Peer Review Version

Author Accepted Manuscript

$$EU(Vaccinating)$$

$$= \beta q(1 - p(\theta)(1 - E))u\left(h - c - \frac{\delta(\theta)}{\beta q}\right) + (1 - \beta)q(1$$

$$- p(\theta)(1 - E))u\left(h - c + \frac{\delta(\theta)}{(1 - \beta)q}\right) + (1 - q)\big(1 - p(\theta)(1 - E)\big)u(h)$$

$$+ (p(\theta)(1 - E))\frac{q}{2}u\left(h - l - c - \frac{\delta(\theta)}{\beta q}\right)$$

$$+ (p(\theta)(1 - E))\frac{q}{2}u\left(h - l - c + \frac{\delta(\theta)}{(1 - \beta)q}\right) + (1 - q)(p(\theta)(1 - E))u(h - l)$$

$$EU(Not\ Vaccinating) = p(\theta)u(h - l) + (1 - p(\theta))u(h)$$

We need to find $p(\theta)$ at which $EU(Vaccinating) = EU(Not\ Vaccinating)$.

If the $EU(Vaccinating\ with\ either\ of\ the\ vaccines) < EU(not\ Vaccinating)$, there is no point at which $EU(Vaccinating) = EU(Not\ Vaccinating)$, because $EU(not\ Vaccinating)$ increases with an increasing population vaccination rate and $EU(Vaccinating)$ decreases with an increasing population vaccination rate. We know from Lemma 1, $EU(Vaccinating)$ is lower for a new technology vaccine than for a traditional technology vaccine for small $k > 0$.

Suppose $EU(Vaccinating\ with\ traditional\ technology) > EU(not\ vaccinating) > EU(Vaccinating\ with\ new\ technology)$, then there is only a herd immunity threshold for the traditional technology vaccine.

However, when $EU(Vaccinating\ with\ either\ of\ the\ vaccines) > EU(not\ Vaccinating)$, then from Lemma 1 as $EU(Vaccinating\ with\ traditional\ technology) > EU(Vaccinating\ with\ new\ technology)$, as $EU(not\ Vaccinating)$ increases with decreasing $p(\theta)$ (or increasing θ), the $p(\theta)$ at which $EU(Vaccinating) = EU(not\ Vaccinating)$ is smaller for a new than a traditional technology vaccine.

Peer Review Version

Author Accepted Manuscript

Simulations

We provide two simulations that complement the simulations of the main text. In the first simulation below (Figure W1) we show that when the utility function is less concave ($u(x) = x^{0.8}$) than the utility function in the main text (Figure 2, $u(x) = x^{0.5}$), the U_N is 0.005 units lower than U_T. This is smaller compared to the simulation in Figure 2 in the main text and indicates that when consumers are less risk averse, the efficacy premium decreases.

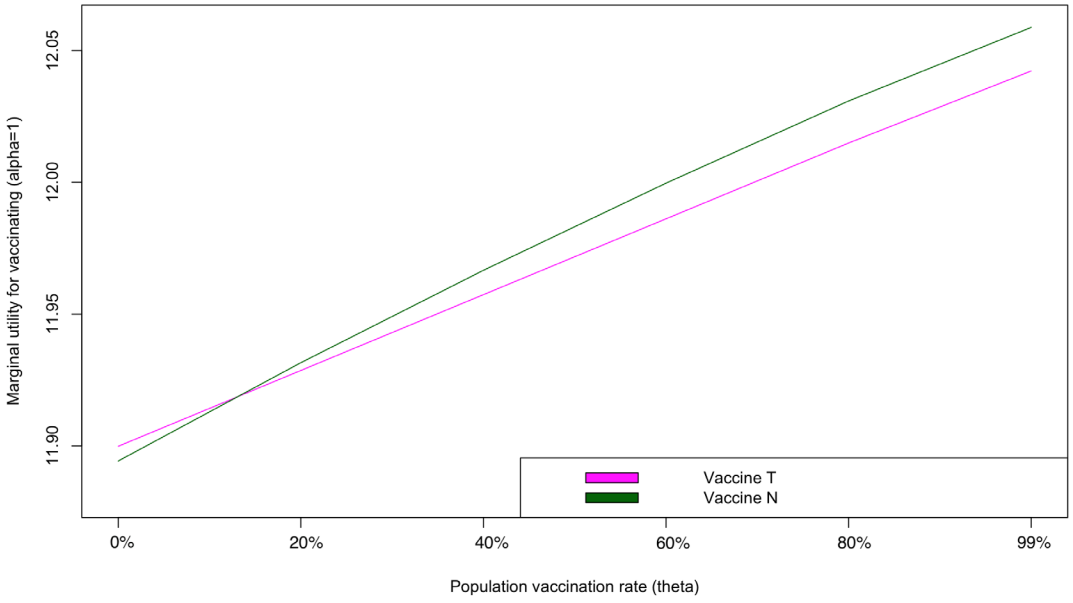


Figure W1. Marginal utility to vaccinate (Parameters: h = 200, l = 120, E_N = 0.851, E_T = 0.85 $u(x) = x^{0.8}$, c = 40, p(0) = 0.25, p(θ) = 0.9-0.001θ (small herd immunity effect), q = 0.1, $\beta = 0.49$, $\bar{u} = 0.2\theta$ (utility for conforming), $\delta_N = 35$ $\delta_T = 0.5$).

In Figure W2, we simulate the marginal utility to vaccinate for a new and a traditional technology vaccine when the herd immunity effect is strong: p(θ) = 0.25-0.25θ (p = 0.25 when θ = 0 and p is 0 when θ = 1). We illustrate Lemma 3 by showing that the herd immunity threshold for the new technology vaccine is lower than for the traditional technology vaccine. The marginal utility to vaccinate for vaccine N(ew) and T(raditional) is simulated for the following parameters. Prelec

Author Accepted Manuscript

weighting function: alpha = 0.4, h = 200, l = 120, $E_N = E_T = 0.85$, u(x) = $x^{0.5}$, c = 40, p(θ) = 0.25-0.25θ (strong herd immunity effect), q = 0.1, vaccine N: $\delta_N = 35$, vaccine T: $\delta_T = 0.5$

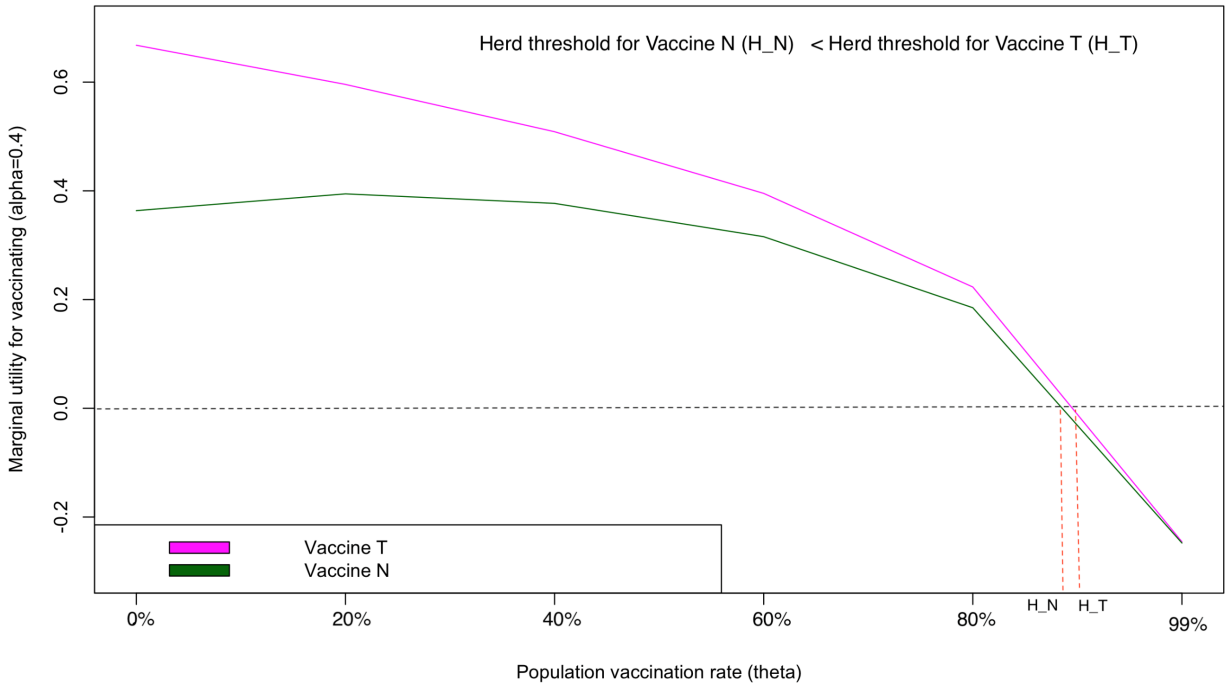


Figure W2. Simulation of marginal utility to vaccinate for vaccine N(ew) and T(raditional).

Review Version

Author Accepted Manuscript

Web Appendix B: Supplementary Material for Study 1a to Study 3

Study 1a – Supplementary Material

We predicted the efficacy premium with linear regression models to test H2a. Concern about side effects of the new versus traditional technology vaccine was positively related to the efficacy premium (model 1, table W1). Trust in government and regulatory processes was negatively associated with the premium, providing support for H2a. We controlled for demographics (older individuals tended to have a higher efficacy premium) and regular flu vaccination. In model 2, we also controlled for COVID-19 risk and severity perceptions (model 2, table W1) but this did not affect our key findings.

Peer Review Version

Author Accepted Manuscript

Table W1. Side effects and trust are concerns for new technologies.

	Dependent variable: Efficacy premium	
	Model 1	Model 2
Concern about side effects (new-traditional)	4.265 *** (1.208)	4.234*** (1.211)
Trust in government and regulatory processes	-3.147*** (.956)	-2.941*** (.970)
Gender (female)	3.029 (2.556)	2.835 (2.601)
Age	.189*** (.091)	.226*** (.097)
No regular flu vaccine	2.785 (2.855)	2.172 (2.893)
Frontline worker	1.392 (3.609)	1.463 (3.642)
Caucasian/white	-.975 (1.271)	-.77 (1.296)
COVID-19 risk perception		-.259 (.993)
COVID-19 severity perception		-.879 (.900)
COVID-19 affect life		-.597 (.762)
Constant	13.952 (12.48)	19.024 (13.053)
Observations	115	115
R^2	.308	.326
Adjusted R^2	.263	.261
Residual Std. Error	12.555 (df = 107)	12.572 (df = 104)
F Statistic	6.818*** (df = 7; 107)	5.030*** (df = 10; 104)

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

Peer Review Version

Author Accepted Manuscript

Table W2. Study 1a correlation matrix of key variables.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Efficacy premium	1													
(2) COVID-19 risk estimate	-.096	1												
(3) COVID-19 severity	-.194*	.165	1											
(4) COVID-19 affect life	-.141	.125	.422*	1										
(5) Trust in government & regulatory processes	-.407*	.067	.237*	.143	1									
(6) Concern about side effects (traditional technology)	.300*	-.137	-.037	.048	-.353*	1								
(7) Concern about side effects (new technology)	.488*	-.161	-.091	.019	-.478*	.846*	1							
(8) Female	.152	.084	-.073	-.046	-.061	.185*	.219*	.031	1					
(9) Age	.073	-.066	.331*	.208*	.052	-.038	-.065	.277*	.038	1				
(10) Education	-.029	-.084	-.206*	.002	-.031	-.045	-.104	-.094	.168	-.05	1			
(11) Income	.026	.021	-.048	-.048	-.005	-.152*	-.209*	-.013	.140	.006	.332*	1		
(12) Frontline worker	-.002	.080	.023	.020	-.015	.006	.017	.070	-.062	.147	-.001	-.046	1	
(13) White/Caucasian	-.030	-.109	-.004	-.136	.419*	-.276*	-.265*	-.024	.046	.219*	.008	-.021	.043	1
(14) Regular flu vaccine (yes)	-.232*	.046	.234*	.206*	-.353*	-.146	-.228*	.287*	-.034	.243*	-.013	.064	.190*	.126

* $p < .05$

Peer Review Version

Author Accepted Manuscript

Study 1b – Supplementary Material

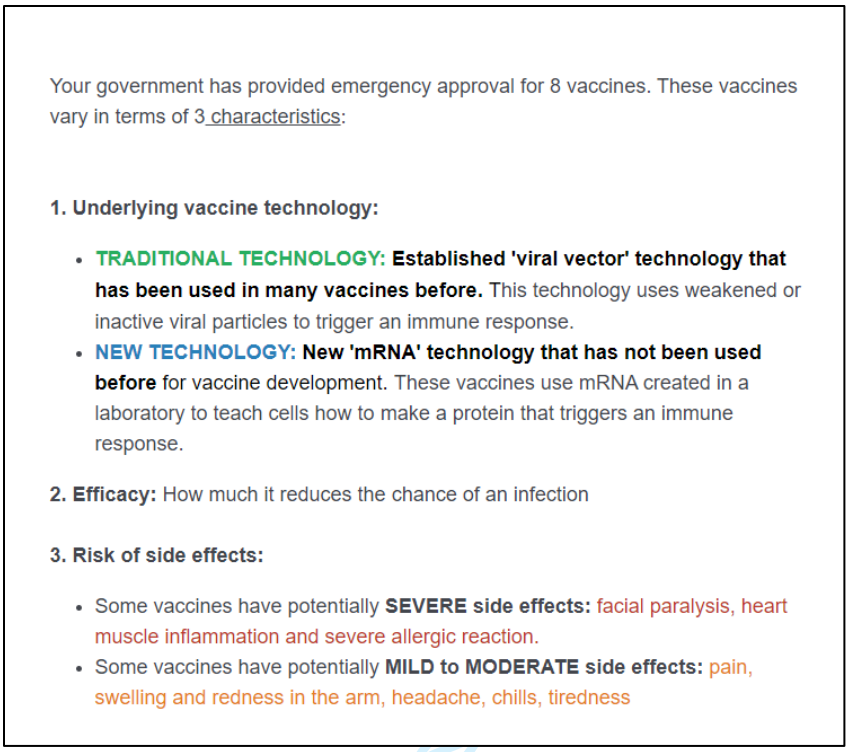


Figure W3. Description of vaccine characteristics.

Table W3. Conjoint vaccine attributes and levels used in study 1b.

Vaccine Attributes	**Levels**
Vaccine Technology	Traditional Technology New Technology
Efficacy (low vs. high)	Reduces chance of infection by: **60%** Reduces chance of infection by: **90%**
Side Effects (small chance of severe side effect vs. mild-moderate side effect)	**0.1%** chance of **SEVERE** side effects (1 in 1000 people) **99.9%** chance of **NO** side effects (999 in 1000 people) **100%** chance of **MILD** to **MODERATE** side effects

Review Version

Author Accepted Manuscript

Table W4. Willingness to pay is lower for new than traditional technology vaccines.

	Dependent Variable: Willingness to Pay		
	Model 1	Model 2	Model 3
New Technology	-1.385***	-1.425**	-1.425**
	(.588)	(.601)	(.601)
90% Efficacy	15.568***	15.602***	15.602***
	(1.025)	(1.042)	(1.043)
Severe side effects	-2.885***	-2.915***	-2.915***
	(0.591)	(.605)	(.605)
Female		-.074	-.130
		(3.988)	(3.903)
Age		.128	-.018
		(.173)	(0.178)
Income		4.546***	2.439*
		(1.434)	(1.470)
White/Caucasian		-2.099	-1.258
		(4.604)	(4.634)
Nr. of COVID-19 vaccines received			2.800**
			(1.356)
No regular flu vaccine			-12.041***
			(4.444)
Constant	30.872***	12.621	35.455***
	(1.814)	(9.516)	(13.030)
Observations	3504	3344	3424
R^2	.031	.037	.084
Adjusted R^2	.03	.034	.081
Residual Std. Error	44.487 (df = 3500)	44.438 (df = 3332)	43.543 (df = 3414)
F Statistic	37.272*** (df =3; 3500)	11.671*** (df =11; 3332)	34.577*** (df = 9; 3414)

*Note: *p < .05; **p < .01; ***p < .001*

Peer Review Version

Author Accepted Manuscript

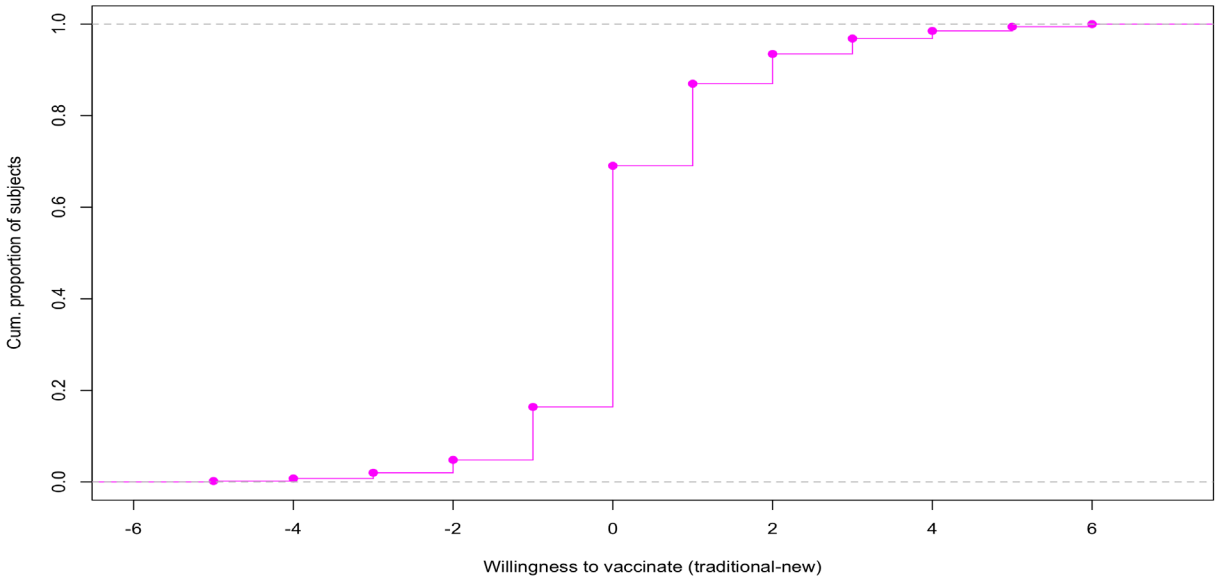


Figure W4. Cumulative distribution of the willingness to vaccinate premium.

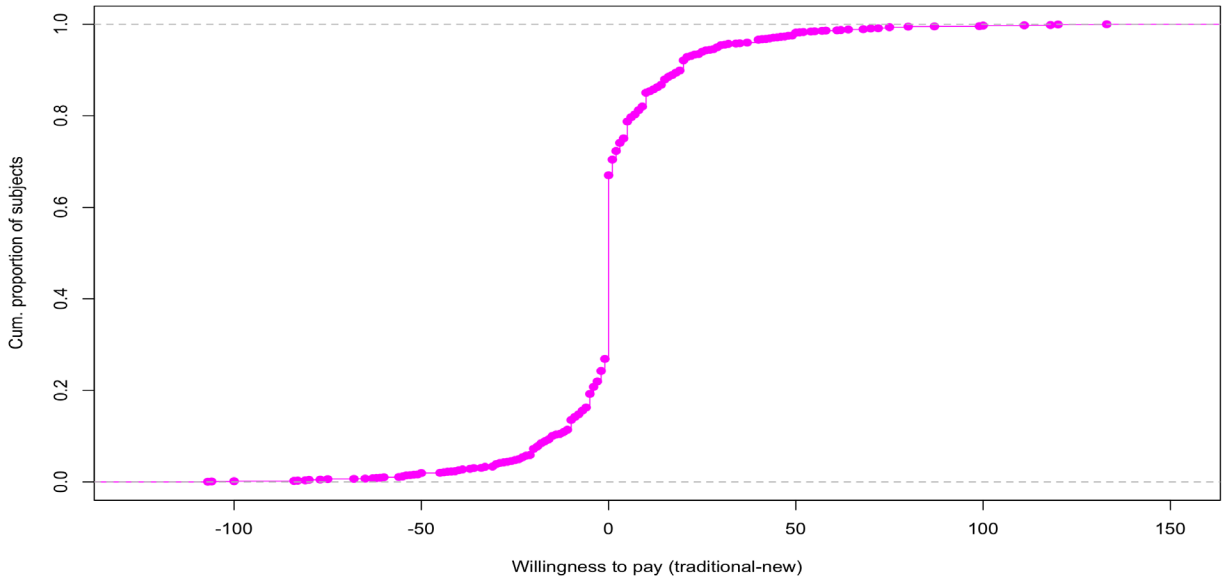


Figure W5. Cumulative distribution of the willingness to pay premium.

Author Accepted Manuscript

Table W5. Higher trust in government is associated with less aversion to new technology.

	Dependent Variable: Premium willingness to vaccinate		
	Model 1	Model 2	Model 3
Trust in government	-.107***	-.105***	-.079**
	(.026)	(.027)	(.029)
Trust in science	.007	.007	.004
	(.025)	(.026)	(.028)
Female		.043	.038
		(.092)	(.091)
Age		-.000	-.002
		(.003)	(.004)
Income		-.024	-.002
		(.032)	(.034)
White/Caucasian		.075	.068
		(.119)	(.118)
Nr. of COVID-19 vaccines received			-.123**
			(.043)
No regular flu vaccine			-.004
			(.111)
Constant	.654***	.699**	.583*
	(.156)	(.256)	(.293)
Observations	438	427	427
R^2	.036	.039	.061
Adjusted R^2	.031	.026	.043
Residual Std. Error	383.913 (df = 435)	380.144 (df = 420)	371.772 (df = 418)
F Statistic	8.15*** (df =2; 435)	2.91** (df = 6; 420)	3.40*** (df = 8; 418)

*Note: *p < .05; **p < .01; ***p < .001*

Peer Review Version

Author Accepted Manuscript

Table W6. Higher technology readiness is associated with less aversion to new technology vaccines.[1]

	Dependent Variable: Premium willingness to vaccinate		
	Model 1	Model 2	Model 3
TR middle tier	-.329* (.140)	-.326* (.147)	-.305* (.146)
TR high tier	-.136 (.125)	-.121 (.130)	.056 (.129)
Female		.038 (.093)	.039 (.092)
Age		-.002 (.004)	.001 (.004)
Income		-.034 (.032)	.002 (.034)
White/Caucasian		.091 (.120)	.079 (.118)
Nr. of COVID-19 vaccines received			-.135*** (.038)
No regular flu vaccine			.026 (.110)
Constant	.480*** (.109)	.631** (.246)	.701* (.289)
Observations	438	427	427
R^2	.013	.019	.055
Adjusted R^2	.008	.005	.037
Residual Std. Error	392.938 (df = 437)	388.382 (df = 420)	373.956 (df = 418)
F Statistic	2.97 (df =2; 435)	1.36 (df = 6; 420)	3.40*** (df = 8; 418)

*Note: *p < .05; **p < .01; ***p < .001*

[1] The Technology Readiness Index 2.0 is copyrighted by A. Parasuraman and Rockbridge Associates, Inc., 2014. This scale may be duplicated only with written permission from the authors.

Peer Review Version

Author Accepted Manuscript

Study 2 – Supplementary Material

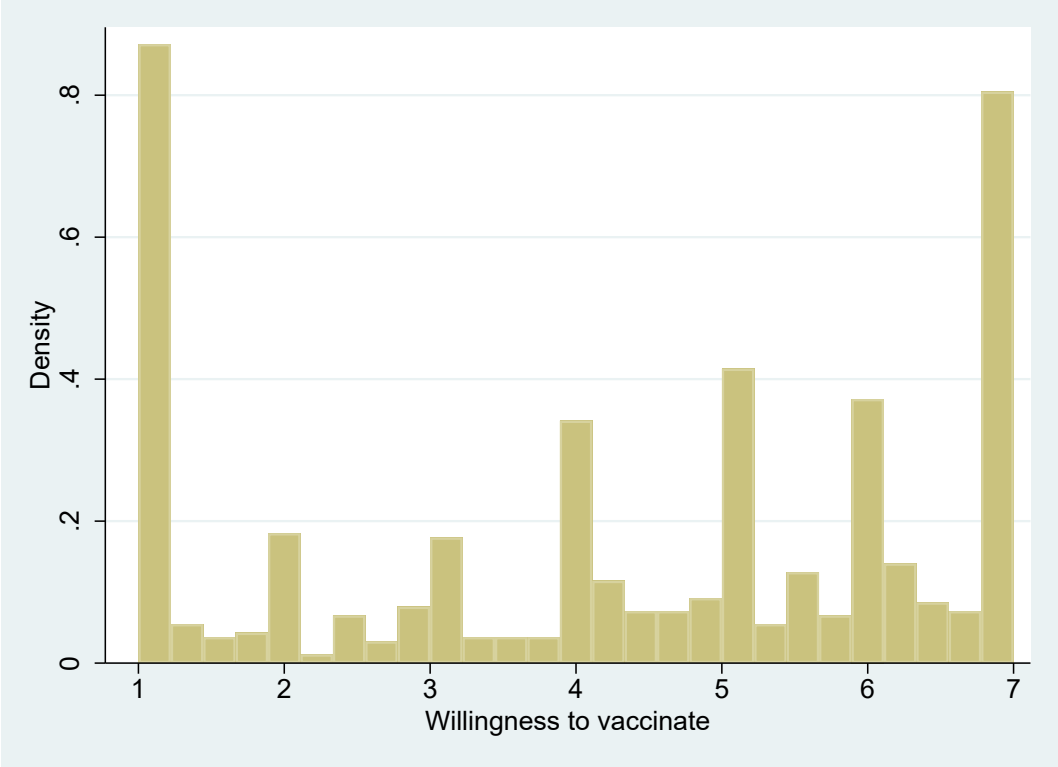


Figure W6. Histogram of willingness to vaccinate.

The social proof nudge had a positive effect on willingness to vaccinate. There was a significant increase in willingness to vaccinate, when comparing the 0% (Med = 3.07, SD = 2.16) versus all other population vaccination levels (30%: Med = 5.01, SD = 2.12; 60%: Med = 5.00, SD = 2.01; 90%: Med = 5.06, SD = 2.17; all *p*s < .001).

Author Accepted Manuscript

Table W7. Willingness to pay for insurance including new technology is lower than for insurance including traditional technology vaccine.

	Dependent variable: Willingness to pay for insurance (log (x+1) transformed)
New technology condition	-.786**
	(.304)
Social proof nudge: 30%	.073
	(.304)
Social proof nudge: 60%	-.028
	(.306)
Social proof nudge: 90%	.221
	(.307)
New technology x 30%	(.182)
	(.427)
New technology x 60%	.423
	(.431)
New technology x 90%	.200
	(.432)
Age	-.017**
	(.006)
Gender (Female)	-.394*
	(.154)
Income	-.020
	(.058)
Education	.321***
	(.067)
White/Caucasian	-.102
	(.176)
Nr. of COVID-19 vaccinations	.341***
	(.064)
No regular flu vaccine	-.592***
	(.175)
Constant	3.573***
	(.464)
Observations	710
R^2	.174
Adjusted R^2	.158
Residual Std. Error	2835 (df = 695)
F Statistic	10.51*** (df = 14; 695)

*Note: *p < .05; **p < .01; ***p < .001*

Peer Review Version

Author Accepted Manuscript

Table W8. Willingness to pay to switch from new to traditional technology vaccine is higher than vice versa.

	Dependent variable: Willingness to pay to switch vaccine
New technology condition	16.873*
	(7.943)
Social proof nudge: 30%	2.242
	(7.936)
Social proof nudge: 60%	11.260
	(7.886)
Social proof nudge: 90%	-3.684
	(8.161)
New technology x 30%	-17.164
	(11.234)
New technology x 60%	-22.468
	(11.152)
New technology x 90%	.261
	(11.278)
Baseline willingness to pay for insurance package (log (1+x))	9.474***
	(1.040)
Constant	-58.057***
	(8.225)
Variance	2177.738
	(194.096)
Observations	738
Pseudo R^2	.0251

*Note: *p < .05; **p < .01; ***p < .001*

Participants rated the infection risk with a vaccine (M = 3.13, SD = 1.59) as significantly lower than without a vaccine (M = 4.12, SD = 1.56, t(737) = -13.12, $p < .001$, d = .63). They also rated the severity of illness as significantly lower with a vaccine (M = 3.20, SD = 1.39) than without a vaccine (M = 4.64, SD = 1.46, t(737) = 19.76, $p < .001$, d = 1.01). Two-way ANOVAs on the difference scores (infection risk with vaccine MINUS infection risk without vaccine; severity of

Peer Review Version

Author Accepted Manuscript

illness with vaccine MINUS severity of illness without vaccine) showed that the vaccine technology and the social proof nudge had no effect on the perceived reduction of infection risk and severity of illness. Neither was there an interaction effect (all *p*s = ns). This indicates that the aversion to new technology vaccines and reduction via the social proof nudge was not driven by differences in perceived effectiveness and infection risk after vaccinating.

Results regarding the uncertainty of side effect are consistent with H3a. The new technology vaccine was perceived as more uncertain (M = 4.65, SD = 1.75) than the traditional technology vaccine (M = 4.04, SD = 1.78, t(736) = -4.66, $p < .001$, d = .34). This difference was reduced as the population vaccination rate increased (see Figure W7). At the 0% and 30% population vaccination rate, the new technology vaccine was perceived as significantly more uncertain ($p = .002$, and $p < .001$). This difference was only marginally significant at the 60% vaccination rate ($p = .060$) and non-significant at the 90% vaccination rate ($p = .350$). The results remain consistent when including demographic controls.

Peer Review Ve

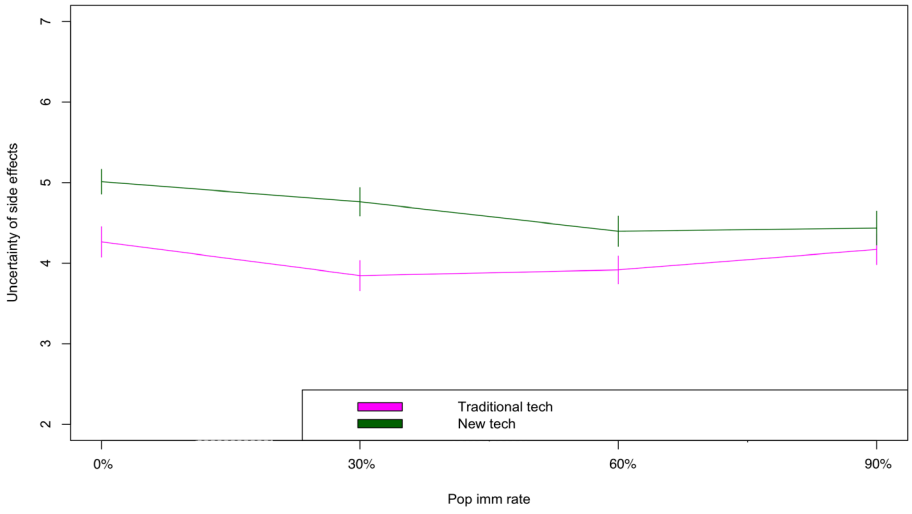


Figure W7. Perceived uncertainty of side effects across conditions.

Author Accepted Manuscript

Table W9. A higher difference between the population vaccination rate and perceived herd immunity threshold is associated with lower willingness to vaccinate.

	Dependent Variable: Willingness to Vaccinate
Difference: Population vaccination rate - Herd immunity threshold	-.012*** (.005)
New technology vaccine	-.874*** (.300)
New technology vaccine x Difference: Population vaccination rate - Herd immunity threshold	-.008 (.007)
Female	-.460* (.273)
Age	-.015 (.012)
Income	.154 (.102)
Education	.128 (.117)
White/Caucasian	-.147 (.313)
Constant	3.327*** (.728)
Observations	710
Pseudo R^2	.0482

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

Peer Review Version

Author Accepted Manuscript

Table W10. Higher TR is associated with higher willingness to vaccinate in the new technology condition.

	Dependent variable:
	Willingness to Vaccinate
New Technology Vaccine	-4.186**
	(1.404)
TR score	.346
	(.270)
New Technology x TR score	1.063**
	(.399)
Social Proof Nudge: 30%	1.297***
	(.344)
Social Proof Nudge: 60%	1.386***
	(.346)
Social Proof Nudge: 90%	1.655***
	(.347)
Constant	2.486*
	(.975)
Observations	738
Pseudo R-squared	.074

*Note: *p < .05; **p < .01; ***p < .001*

Peer Review Version

Author Accepted Manuscript

Table W11. High TR segment has lower aversion to new technology vaccine.

	Dependent variable: Willingness to vaccinate
TR middle tier	.130
	(.651)
TR high tier	.830
	(.595)
New technology vaccine	-2.150**
	(.805)
New technology x TR middle tier	1.73
	(.950)
New technology x TR high tier	1.75*
	(.870)
Social Proof Nudge: 30%	1.4***
	(.369)
Social Proof Nudge: 60%	1.42***
	(.370)
Social Proof Nudge: 90%	1.51***
	(.371)
Constant	3.15***
	(.594)
Observations	738
Pseudo R-squared	.0797

*Note: *p < .05; **p < .01; ***p < .001*

Peer Review Version

Author Accepted Manuscript

Table W12. TR score is negatively associated with willingness to switch from new to traditional technology vaccine.

	Dependent variable: Willingness to pay to switch
TR score	-16.145***
	(4.843)
Social Proof Nudge: 30%	-13.295
	(7.607)
Social Proof Nudge: 60%	-4.320
	(7.550)
Social Proof Nudge: 90%	.656
	(7.492)
Baseline log (1+x) WTP for health insurance package	6.880***
	(1.269)
Age	-.530*
	(.231)
Female	2.823
	(5.520)
Income	-1.111
	(2.011)
Education	3.590
	(2.385)
White/Caucasian	15.460*
	(6.491)
Constant	21.643
	(22.814)
Observations	353
Pseudo R-squared	.031

*Note: *p < .05; **p < .01; ***p < .001*

Peer Review Version

Author Accepted Manuscript

Study 3 – Supplementary Material

In the pesticide context, a higher proportion of participants indicated not wanting either of the two options (new or traditional technology) when compared to all other contexts (see table W13, base is the bacterial infection treatment).

Peer Review Version

Table W13. Rejection of both products (new and traditional) is higher in the pesticide context.

	Dependent variable: Not wanting either product (0/1)
Context: Car	-.420
	(.025)
Context: Energy	-.036
	(.025)
Context: Pesticide	.098***
	(.025)
Constant	.198***
	(.018)
Observations	1996
R2	.019
Adjusted R2	.018
Residual Std. Error	.399 (df = 1992)
F Statistic	13.18*** (df = 3; 1992)

*Note: *p < .05; **p < .01; ***p < .001*

The average preference ratings aggregating over all contexts are as follows: at 0%, M = 28.26 (< 50, $p < .001$), at 30%, M = 36.12 (< 50, $p < .001$), at 60%, M = 43.22 (< 50, $p < .001$), and at 90%, M = 47.11 (< 50, $p < .001$).

Author Accepted Manuscript

Table W14. Social proof nudge increases preference for new technology option in all contexts.

	Dependent variable: Preference for new technology	
	Model 1	Model 2
Social proof nudge 30%	7.929***	8.355***
	(1.985)	(1.960)
Social proof nudge 60%	14.806***	14.947***
	(2.390)	(2.341)
Social proof nudge 90%	18.690***	18.729***
	(2.425)	(2.393)
Context: Car	4.374***	4.291**
	(1.949)	(1.945)
Context: Energy	4.744***	4.634***
	(1.765)	(1.764)
Context: Pesticide	-.182	-.353
	(1.779)	(1.773)
Gender (female)		-9.145***
		(2.144)
Age		-.235**
		(.098)
Caucasian/White		1.712
		(2.505)
Constant	25.957***	39.128***
	(1.976)	(4.457)
Observations	1590	1590
R2	.055	.082
Adjusted R2	.051	.077
Residual Std. Error	31.147 (df = 1583)	30.723 (df = 1580)
F Statistic	15.219*** (df = 6; 1583)	15.647*** (df = 9; 1580)

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

Peer Review Version

Author Accepted Manuscript

Table W15. Social proof nudge reduces aversion to new technology by reducing perceived uncertainty.

Social proof nudge	Non-antibiotic treatment		Nano-pesticide		Lithium battery car		Hydrogen heating	
	Product rating	Perceived uncertainty	Product rating	Perceived uncertainty	Product rating	Perceived uncertainty	Product rating	Perceived uncertainty
0% condition	M = 24.89 SD = 25.88	M = 5.32 SD = 1.32	M = 30.90 SD = 29.43	M = 5.16 SD = 1.56	M = 29.84 SD = 34.87	M = 5.35 SD = 1.67	M = 27.34 SD = 26.72	M = 4.99 SD = 1.36
	t(88)=-9.15, p<.001		t(89)=-6.16, p<.001		t(94)=-5.63, p<.001		t(94)=-8.27, p<.001	
30% condition	M = 32.63 SD = 27.94	M = 4.74 SD = 1.08	M = 31.85 SD = 29.70	M = 5.21 SD = 1.30	M = 37.42 SD = 31.11	M = 4.89 SD = 1.60	M = 41.57 SD = 29.25	M = 4.73 SD = 1.37
	t(104)=-6.37, p<.001		t(92)=-5.89, p<.001		t(104)=-4.14, p<.001		t(92)=-2.78, p=.007	
60% condition	M = 42.77 SD = 32.44	M = 4.60 SD = 1.42	M = 39.17 SD = 30.61	M = 4.73 SD = 1.45	M = 48.12 SD = 33.85	M = 4.40 SD = 1.69	M = 42.16 SD = 30.38	M = 4.73 SD = 1.44
	t(99)=-2.23, p=.028		t(91)=-3.39, p=.001		t(110)=-0.59, p=.559		t(119)=-2.83, p=.006	
90% condition	M = 44.58 SD = 31.92	M = 4.40 SD = 1.34	M = 41.96 SD = 31.62	M = 4.88 SD = 1.50	M = 47.13 SD = 33.85	M = 4.44 SD = 1.71	M = 53.08 SD = 32.00	M = 4.22 SD = 1.57
	t(106)=-1.76, p=.082		t(76)=-2.23, p=.028		t(110)=-0.82, p=.413		t(110)=1.01, p=.313	
Main effect	F(3, 397) = 9.20, p < .001	F(3, 397) = 8.90, p < .001	F(3, 348) = 2.75, p = .042	F(3, 348) = 2.26, p = .084	F(3, 418) = 6.54, p < .001	F(3, 418) = 6.80, p < .001	F(3, 415) = 12.77, p < .001	F(3, 415) = 5.34, p = .001
Indirect effect	b = 3.94, SE = 0.88, CI^{95}[2.21, 5.67]		b = 1.78, SE = 0.98, CI^{95}[-0.14, 3.71]		b = 3.84, SE = 0.97, CI^{95}[1.93, 5.76]		b = 3.10, SE = 0.87, CI^{95}[1.39, 4.81]	

Note: t-test indicates difference from scale mid-point 50, F-test indicates main effect of social proof nudge, mediation results indicate indirect effect of social proof nudge on product rating via perceived uncertainty.

Peer review version

Author Accepted Manuscript

Table W16. Social proof nudge increases odds of signing up to mailing list (non-antibiotic treatment).

	Dependent variable: Sign-up to mailing list (0/1)
Social Proof Nudge	.206*
	(.102)
Constant	-1.281***
	(.204)
Observations	401
Chi^2	4.14
$Prob>Chi^2$	.0420
Pseudo R^2	.0087
Log Likelihood	-235.441

*Note: *p < .05; **p < .01; ***p < .001*

Table W17. Social proof nudge increases odds of downloading article (nano-pesticide).

	Dependent variable: Downloading article (0/1)
Social Proof Nudge	.264*
	(.119)
Constant	-1.679***
	(.233)
Observations	352
Chi^2	4.97
$Prob>Chi^2$	.026
Pseudo R^2	.013
Log Likelihood	-182.428

*Note: *p < .05; **p < .01; ***p < .001*

Peer Review Version

Author Accepted Manuscript

Table W18. Social proof nudge marginally increases time spent on map (lithium-battery car).

	Dependent variable: Time spent on map
Social Proof Nudge	7.223
	(3.923)
Constant	18.530*
	(7.772)
Observations	65
R^2	.051
Adjusted R^2	.036
F (1, 63)	3.39
RMSE	33.346

*Note: *p < .05; **p < .01; ***p < .001*

Table W19. Social proof nudge has no effect on sign-up for brochure (hydrogen heating).

	Dependent variable: Sign-up for brochure (0/1)
Social Proof Nudge	.209
	(.150)
Constant	-.521***
	(.313)
Observations	419
Chi^2	2.00
Prob>Chi^2	.158
Pseudo R^2	.007
Log Likelihood	-137.612

*Note: *p<0.05; **p<0.01; ***p<0.001*

Table W20. TR score, trust in government and risk seeking are correlated with preference for new technology in all product contexts.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
(1) Non-antibiotic treatment						
(2) Nano-pesticide	.380*					
(3) Lithium-battery car	.260*	.329*				
(4) Hydrogen technology	.289*	.328*	.495*			
(5) TR score	.174*	.244*	.251*	.168*		
(6) Trust in government	.183*	.171*	.282*	.217*	.268*	
(7) Self-rated risk seeking	.195*	.243*	.228*	.221*	.252*	.323*

*Note: * p < .05*

Peer Review Version

Author Accepted Manuscript

Table W21. Trust in government predicts preference for new technology.

	Dependent variable: Preference for new technology
Trust in government	4.839*** (.730)
Social proof nudge: 30%	8.244*** (2.018)
Social proof nudge: 60%	15.505*** (2.287)
Social proof nudge: 90%	18.630*** (2.341)
Context: Car	4.139** (1.934)
Context: Energy	4.661*** (1.768)
Context: Pesticide	-.975 (1.760)
Gender (female)	-9.431*** (2.047)
Age	-.184** (.094)
White / Caucasian	1.804 (2.292)
Constant	22.180*** (4.890)
Observations	1590
R2	.130
Adjusted R2	.125
Residual Std. Error	29.914 (df = 1579)
F Statistic	23.612*** (df = 10; 1579)

*Note: *p < .05; **p < .01; ***p < .001*

Peer Review Version

Author Accepted Manuscript

Table W22. TR score predicts preference for new technology.

	Dependent variable: Preference for new technology
Technology readiness score	8.623*** (1.483)
Social proof nudge: 30%	8.657*** (1.962)
Social proof nudge: 60%	15.532*** (2.301)
Social proof nudge: 90%	18.614*** (2.362)
Context: Car	4.338** (1.946)
Context: Energy	4.735*** (1.765)
Context: Pesticide	-.656 (1.771)
Gender (female)	-6.776*** (2.120)
Age	-.206** (.093)
White	1.287 (2.401)
Constant	7.945 (6.821)
Observations	1590
R2	.115
Adjusted R2	.110
Residual Std. Error	30.167 (df = 1579)
F Statistic	20.578*** (df = 10; 1579)

*Note: *p < .05; **p < .01; ***p < .001*

Peer Review Version

Author Accepted Manuscript

Table W23. TR segments predict preference for new technology.

	Dependent variable: Preference for new technology
Technology readiness segment (low)	-14.963***
	(2.799)
Technology readiness segment (medium)	-5.032**
	(2.408)
Social proof nudge: 30%	8.259***
	(1.949)
Social proof nudge: 60%	15.128***
	(2.312)
Social proof nudge: 90%	18.195***
	(2.372)
Context: Car	4.255**
	(1.948)
Context: Energy	4.639***
	(1.766)
Context: Pesticide	-0.638
	(1.771)
Gender (female)	-6.986***
	(2.106)
Age	-.228**
	(.094)
White / Caucasian	1.707
	(2.401)
Constant	42.037***
	(4.453)
Observations	1590
R2	.111
Adjusted R2	.105
Residual Std. Error	30.254 (df = 1578)
F Statistic	17.872*** (df = 11; 1578)

*Note: *p < .05; **p < .01; ***p < .001*

Peer Review Version

Author Accepted Manuscript

Table W24. Risk-seeking predicts preference for new technology.

	Dependent variable: Preference for new technology
Risk seeking (self-rated)	2.620***
	(.437)
Social proof nudge: 30%	8.286***
	(1.961)
Social proof nudge: 60%	14.804***
	(2.317)
Social proof nudge: 90%	19.089***
	(2.367)
Context: Car	4.022**
	(1.943)
Context: Energy	4.430**
	(1.756)
Context: Pesticide	-.601
	(1.760)
Gender (female)	-5.668***
	(2.141)
Age	-.204**
	(.096)
White / Caucasian	2.251
	(2.451)
Constant	25.225***
	(5.213)
Observations	1590
R2	.116
Adjusted R2	.110
Residual Std. Error	30.159 (df = 1579)
F Statistic	20.672*** (df = 10; 1579)

*Note: *p < .05; **p < .01; ***p < .001*

Peer Review Version

Author Accepted Manuscript

Table W25. Selection of riskier treatment option predicts preference for new technology.

	Dependent variable: Preference for new technology
Treatment preference: Indifferent	-.740
	(2.371)
Treatment preference: Risky option	7.523**
	(3.470)
Social proof nudge: 30%	7.925***
	(1.951)
Social proof nudge: 60%	14.636***
	(2.332)
Social proof nudge: 90%	18.514***
	(2.392)
Context: Car	4.127**
	(1.953)
Context: Energy	4.576***
	(1.768)
Context: Pesticide	-.440
	(1.771)
Gender (female)	-9.206***
	(2.143)
Age	-.239**
	(.098)
White / Caucasian	2.039
	(2.493)
Constant	38.917***
	(4.495)
Observations	1590
R2	.087
Adjusted R2	.081
Residual Std. Error	30.657 (df = 1578)
F Statistic	13.655*** (df = 11; 1578)

*Note: *p < .05; **p < .01; ***p < .001*

Peer Review Version

Author Accepted Manuscript

Web Appendix C: Additional Studies

Supplementary Study 1 – Pilot Test of Stimuli

The aim of this pilot was to test the assumption that consumers perceive a new technology vaccine as more uncertain than a traditional technology vaccine, specifically its potential side effects.

Methodology

Participants completed an online survey about COVID-19 and potential vaccines. After providing consent, participants were told to imagine that two COVID-19 vaccines were currently available and were provided with information about each. The *traditional technology vaccine* was described as having an efficacy of 70% in preventing the disease. Participants were told that this vaccine uses an established viral vector technology that has been used in many vaccines before. The *new technology vaccine* was described as having an efficacy of 90%. We used 70% and 90% efficacy for the traditional and new technology vaccine, respectively, to resemble their real world efficacy. Participants were told that this vaccine uses a new mRNA technology that has not been used before for vaccine development. Both vaccines had received temporary authorization for emergency use after evaluating the available data. Importantly, participants were told that no serious safety concerns were reported for either vaccine.

After reading the descriptions, participants were randomly assigned to one of two between-subjects conditions (new vs. traditional technology vaccine) and evaluated one of the vaccines. Specifically, they evaluated how uncertain they thought the potential side effects of the vaccine were (1 = not uncertain, to 7 = very uncertain) and secondly, how effective they thought the vaccine

Peer Review Version

Author Accepted Manuscript

was in preventing the disease (1 - 7 scale). This latter question was included to rule out the possibility that individuals might feel more uncertain about the efficacy of a new technology vaccine (rather than its side effects).

Finally, participants answered questions regarding their age, gender, country of residence, education and income, occupation (including front line worker status) and ethnicity. We also asked whether they regularly took flu vaccinations (yes, no).

Sample

We recruited a sample of eighty participants residing in the UK via Prolific (prolific.co). See Table W26 for demographics for all supplementary studies.

Table W26. Samples reflect a wide range of demographic factors in supplementary studies 1 - 5.

	Study 1	**Study 2**	**Study 3**	**Study 4**	**Study 5**
Recruitment	Prolific	Prolific	Students	CloudResearch	CloudResearch
Sample Size	80	149	129	166	120
Female	48.75%	70.47%	48.06%	37.95%	45.83%
Ethnicity (Caucasian)	85.00%	82.55%		71.69%	
Age (in years)	*M* = 34.03 *SD* = 10.7 Range = 18 - 61	*M* = 34.84 *SD* = 11.08 Range = 18 - 63	*M* = 29.16 *SD* = 3.17 Range = 21 -43	*M* = *41.76* *SD* = *12.39* Range = 20 -77	*M* = 43.22 *SD* = 12.41 Range = 22 - 77
Education (Median)	High-school graduate / A Level	Bachelor's degree	MBA students	Bachelor's degree	Bachelor's degree
Income (Median)	£40k-£60k	£20k-£40k	-	$25k-$49,999	$50k-$74,999
Occupation	Management & professional (22.50%)	Unemployed (29.93%)	-	Management & professional (30.72%)	Management & professional (39.17%)
	Sales and office (16.25%)	Management & professional (28.57%)	-	Service industry (19.28%)	Service industry (17.50%)
	Unemployed (13.75%)	Service industry (12.24%)	NA	Sales and office (18.07%)	Unemployed (10.83%)
Frontline Worker	15%	12.08%	NA	NA	NA

Author Accepted Manuscript

Results

Participants perceived the side effects of the new technology vaccine to be significantly more uncertain than those of the traditional technology vaccine (M_{new} = 4.20, $M_{traditional}$ = 3.20, t(78) = 2.77, p = .006, d = .620). Participants accurately evaluated the new technology vaccine to be more effective than the traditional technology vaccine (M_{new} = 5.80, $M_{traditional}$ = 4.87, t(78) = 3.47, p < .001, d = .776).

Discussion

These results confirm our assumption that consumers perceive new technology vaccines as more uncertain than traditional technology vaccines, specifically their potential side effects—despite being told that there are no serious safety concerns. Conversely, the efficacy of the new technology vaccine was correctly evaluated as being higher, in line with the provided information.

Supplementary Study 2 – Within-Subjects Experiment

The aim of this study was to test if providing a social proof nudge, in form of an increasing population vaccination rate, can reduce aversion towards new technology vaccines. We expected a positive impact of the social proof nudge for both vaccine types, but a stronger positive effect for the new technology vaccine.

Methodology

We employed a 2 (vaccine type: traditional technology vs. new technology) x 6 (social proof nudge: 1%, 25%, 50%, 65%, 80%, 95% population vaccination rate) mixed design, with vaccine type as the between-subjects factor.

Participants completed a survey about COVID-19 and attitudes towards potential vaccines. Participants first completed the same COVID-19 filter and risk perception questions as previously. Next, participants were informed about two COVID-19 vaccines (*traditional technology vaccine*

Peer Review Version

Author Accepted Manuscript

and *new technology vaccine)*. The vaccine descriptions were the same as before. After seeing the information, participants were randomly assigned to one of two between-subjects conditions.

In the *traditional technology condition*, participants were informed that they were offered the traditional technology vaccine and indicated their willingness to vaccinate for six within-subjects scenarios (1 = not at all, 7 = very much). The scenarios varied in terms of the population vaccination rate ("*About y% of the population in your area have already been vaccinated with the traditional technology vaccine.*"). The population vaccination rate was given as 1%, 15%, 50%, 65%, 80% and 95% in successive order. Participants in the *new technology condition* were informed that they were offered the new technology vaccine and completed the same task.

Next, all participants completed questions regarding concerns about side effects of the vaccine they had been offered, trust in government as well as flu vaccination history. In addition, we measured risk and ambiguity preferences as individual-level difference variables since these might impact vaccine decisions (Blaisdell et al. 2016; Dubov 2015; Han et al. 2018; Ritov and Baron 1990). We elicited risk preferences for gains and losses as well as ambiguity aversion with three incentivized lottery tasks adapting the procedure from (Wakker and Deneffe 1996). Five percent of participants were paid a bonus payment depending on their choices. Finally, participants completed demographic questions.

Sample

We recruited a new sample of one-hundred fifty participants residing in the UK via Prolific. Those who had experienced COVID-19 symptoms or who had already received a COVID-19 vaccination were excluded. Our final sample consisted of 129 participants.

Results

Peer Review Version

Author Accepted Manuscript

A 2 x 6 mixed design ANOVA yielded a marginally significant interaction effect between the social proof nudge and type of vaccine ($F(5, 732) = 1.93$, $p = .087$, $\eta^2 = .013$) and a significant main effect of the social proof nudge ($F(5, 732) = 34.12$, $p < .001$, $\eta^2 = .189$). There was no main effect of the vaccine type ($p = .184$, $\eta^2 = .011$). A test of simple effects to explore the interaction showed the following. For the new technology vaccine, increasing the population vaccination rate had a significant positive effect on willingness to vaccinate for all vaccination levels compared to the baseline (1% vs. 25%: $p = .052$; all others: $p < .001$, see Figure W8).

For the traditional vaccine, increasing the population vaccination rate had a positive effect on willingness to vaccinate for vaccination levels higher than 65% compared to the baseline but not for lower vaccination levels (1% vs. 25%: $p = .870$; 1% vs. 50%: $p = .252$; 1% vs. 65%: $p = 0.035$, 1% vs. 80%: $p < .001$, 1% vs. 95%: $p < .001$). These results confirm our hypothesis that social proof information has a stronger positive effect on willingness to vaccinate for a new than a traditional technology vaccine.

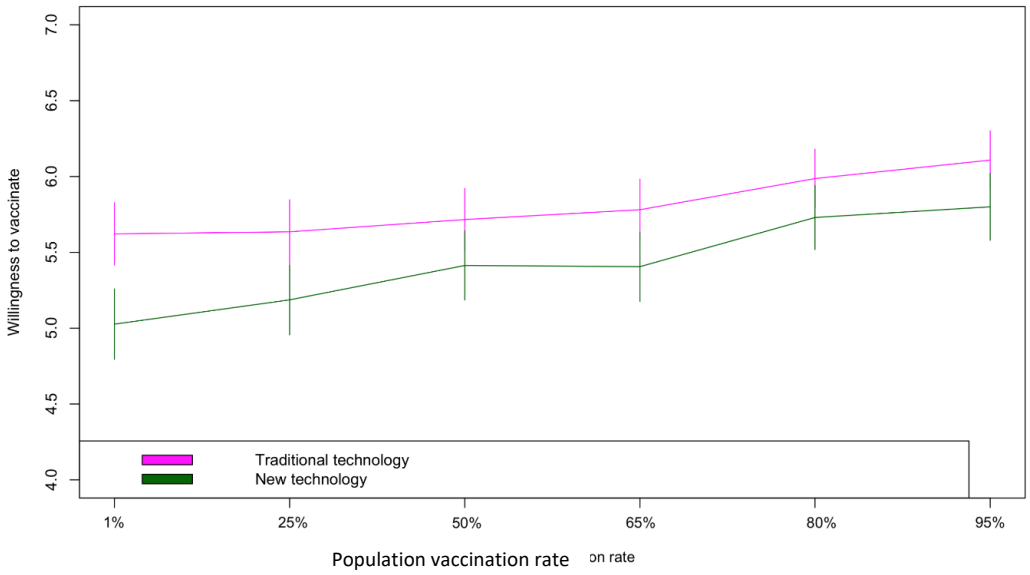


Figure W8. Willingness to vaccinate for increasing population vaccination rates. Standard error bars are shown.

Author Accepted Manuscript

In Table W27, we provide the results of different linear regression models at all levels of the social proof nudge including control variables. At low levels of population vaccination (i.e., 1%), participants in the new technology condition were more averse to vaccinate than in the traditional technology condition. As the population vaccination rate increased, the preference gap between the new and traditional technology vaccine disappeared (e.g., at the 50% population vaccination rate, the coefficients are no longer different). A correlation matrix showing relationships between all key variables measured in the study is shown in Table W28.

Discussion

The results of the previous studies show that consumers are averse towards vaccinating with a new technology vaccine even if it has higher efficacy due to concerns about uncertain side effects. A social proof nudge can reduce this aversion. As the population vaccination rate increases, the difference in the willingness to vaccinate for the traditional and the new technology vaccine disappears. As outlined earlier, in addition to the conformity and social learning mechanisms, we wanted to investigate whether the social proof nudge reduces new technology aversion due to a reduction of uncertainty, and why this might be the case.

Peer Review Version

Author Accepted Manuscript

Table W27. New technology aversion is stronger for lower population vaccination rates.

	Dependent variable: Willingness to Vaccinate					
	1 percent	25 percent	50 percent	65 percent	80 percent	95 percent
	(1)	(2)	(3)	(4)	(5)	(6)
Traditional Vaccine	.755***	.630*	.468	.501	.358	.460
	(.333)	(.341)	(.335)	(.339)	(.313)	(.317)
Ambiguity Aversion	-.103	-.022	-.028	-.039	.007	-.044
	(.070)	(.072)	(.071)	(.071)	(.068)	(.067)
Risk aversion for gains	.042	.020	.039	.037	.028	.036
	(.056)	(.057)	(.056)	(.057)	(.053)	(.053)
Risk aversion for losses	.043	.036	.041	.051	.062	.041
	(.053)	(.054)	(.053)	(.053)	(.050)	(.050)
No regular flu vaccine	-.514	-.513	-.530	-.600	-.623*	-.628*
	(.392)	(.403)	(.395)	(.398)	(.367)	(.374)
COVID-19 risk perception	.138	.042	.056	.038	.051	.084
	(.128)	(.131)	(.129)	(.131)	(.120)	(.122)
Gender (female)	-.138	-.293	-.281	-.275	-.187	-.127
	(.379)	(.389)	(.381)	(.383)	(.356)	(.361)
Age	-.003	-.006	-.012	-.012	-.013	-.014
	(.016)	(.016)	(.016)	(.016)	(.015)	(.015)
Constant	6.003***	7.236***	7.778***	8.043***	8.219***	8.013***
	(1.612)	(1.654)	(1.623)	(1.651)	(1.509)	(1.538)
Observations	125	125	125	125	125	125
R^2	.103	.055	.051	.062	.055	.069
Adjusted R^2	.041	-.010	-.015	-.003	-.011	.005
Residual Std. Error	1.821 (df = 116)	1.869 (df = 116)	1.834 (df = 116)	1.835 (df = 114)	1.703 (df = 115)	1.737 (df = 116)
F Statistic	1.665 (df = 8; 116)	.844 (df = 8; 116)	.772 (df = 8; 116)	.949 (df = 8; 114)	.832 (df = 8; 115)	1.073 (df = 8; 116)

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

Peer Review Version

Author Accepted Manuscript

Table W28. Supplementary study 2 correlation matrix of key variables.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) Willingness to vaccinate	1																
(2) Traditional technology condition	.109*	1															
(3) Population vaccination rate	.961*	.102*	1														
(4) COVID-19 risk perception	.064	-.083*	.057	1													
(5) COVID-19 severity	.182*	-.057	.172*	.437*	1												
(6) COVID-19 affects life	.292*	-.045	.279*	.387*	.428*	1											
(7) Concern about side effects	-.611*	-.185*	-.586*	.205*	.091*	.072*	1										
(8) Trust in government	.180*	.060	.171*	-.011	.054	.001	-.083*	1									
(9) Risk aversion gains	-.070*	.072*	-.060	-.005	-.077*	.042	-.033	.111*	1								
(10) Risk aversion losses	-.09*	-.100*	-.094*	.032	.135*	-.122*	-.140*	-.035	-.028	1							
(11) Ambiguity aversion	-.083*	-.054	-.071*	-.087*	-.113*	-.089*	-.171*	-.049	.414*	.197*	1						
(12) Female	-.045	.055	-.043	.126*	.119*	.155*	.146*	-.028	-.108*	-.202*	-.074*	1					
(13) Age	-.030	-.001	-.031	.098*	.276*	.182*	.158*	.100*	-.127*	.096*	-.014	-.035	1				
(14) Education	-.038	-.069*	-.039	.016	-.047	-.076*	-.046	-.024	-.073*	.110*	.122*	-.042	-.059	1			
(15) Income	-.090*	.010	-.085*	.001	.076*	-.157*	.056	.160*	.090*	-.051	.078*	-.096*	-.080*	.300*	1		
(16) Frontline	-.043	.008	-.042	-.008	-.045	.111*	.181*	.061	-.065	-.119*	.054	-.028	.166*	.109*	-.021	1	
(17) White/Caucasian	-.010	.032	-.007	-.169*	.041	-.067*	.018	-.004	-.031	.012	-.029	.090*	.107*	-.106*	.058	-.044	1
(18) Flu vaccination	.167*	.065	.160*	.103*	.244*	.178*	-.052	-.046	.021	.090*	-.072*	.093*	.172*	.063	.107*	.151*	-.120*

* $p < .05$

Peer Review Version

Author Accepted Manuscript

Supplementary Study 3 – Within-Subjects Experiment with Mediators

The aim of this study was threefold. First, to generalize the findings, we refrained from mentioning COVID-19 and framed the study as a vaccination task for an infectious disease. Instead of Prolific participants, we used a sample of MBA students from an international university. Second, in addition to manipulating the uncertainty of the vaccines by describing the respective technology (i.e., new vs. traditional), we also directly manipulated the uncertainty by giving concrete risk information for experiencing side effects (i.e., in the form of a specific probability) versus uncertain risk information. Third, we investigated potential process mechanisms through which the social proof nudge reduced aversion to new technology. To that end, we included measures of perceived uncertainty, conformity, and social learning.

Methodology

The study was conducted with a sample of 129 MBA students for course credit. After providing informed consent, participants completed a 15-minute online study related to vaccination decision. We employed a 2 (vaccine type: low uncertainty vaccine vs. high uncertainty vaccine) x 4 (social proof nudge: 0%, 30%, 60%, 90% population vaccination rate) mixed design, with vaccine type as between-subjects factor.

Participants were told that there was a new, highly infectious viral disease that could lead to death. Their government had approved two equally effective vaccines and would decide which vaccine was offered to them. They were informed that both vaccines had potentially severe side effects. Vaccine T was devised from a traditional vaccine technology that had been used in many vaccines before. The chance of side effects was described with a concrete probability (i.e., low uncertainty). Vaccine N was devised from a new vaccine technology that had not been used before for vaccine development. The chance of experiencing side effects was described as more uncertain.

Peer Review Version

Author Accepted Manuscript

After seeing this information, participants were randomly assigned to one of the conditions. In the *low uncertainty condition*, participants were informed that the government had decided to provide Vaccine T in their area. They were told it was estimated that people vaccinated with Vaccine T experience severe side effects with a 1% chance. In the *high uncertainty condition*, participants were informed that the government had decided to provide Vaccine N in their area. They were told that the average probability of experiencing severe side effects was estimated to be close to that of vaccine T (1%) but that the exact probability was unclear.

In every round, participants were given the population vaccination rate as 0%, 30%, 60% or 90% and asked whether they would vaccinate with the respective vaccine (I want to vaccinate vs. I remain unvaccinated).

In every round, after participants made their choice, we asked several process related questions. Participants rated the perceived uncertainty of side effects of their respective vaccine (1 = not uncertain, 7 = highly uncertain). This was followed by questions tapping into conformity (*"Do you think others will judge you for your vaccination choice?"* 1 = not at all, 7 = a lot) and social learning *("How knowledgeable do you think others are about the vaccination choice compared to you?"* 1 = less than me, 4 = same as me, 7 = more than me).

We elicited risk preferences for gains as well as ambiguity aversion with two lottery tasks adapting the procedure from Wakker and Deneffe (1996). Finally, participants completed demographic questions (age, gender, country of origin) and questions related to their COVID-19 history (infection in past 6 months, vaccination status, vaccine type).

Results

As our dependent variable was binary, we ran a diff-in-diff logistic regression (base: 0% social proof nudge in the low uncertainty condition) to investigate whether the population

Peer Review Version

Author Accepted Manuscript

vaccination rate had a stronger positive impact on vaccine uptake for the new than the traditional technology vaccine. Figure W9 shows the empirical pattern, Table W29 shows the regression results. We find that at the 0% population vaccination level, participants were less likely to vaccinate in the high uncertainty condition compared to the low uncertainty condition ($\beta = -1.27$, $p = .001$). Increasing the population vaccination rate to 60% and to 90% had a significant positive effect on vaccine uptake compared to the 0% population vaccination level in the low uncertainty condition ($\beta = 1.25$, $p < .001$, and $\beta = 1.62$, $p < .001$).

More importantly, there was a significant interaction between the vaccine condition and social proof nudge at the 30% population vaccination level ($\beta = .58$, $p = .019$). This indicates that there was a significantly higher rate of increase in willingness to vaccinate in the high uncertainty vaccine condition compared to the low uncertainty vaccine condition when the population vaccination rate increased from 0% to 30%. At higher population vaccination levels, there was no differential increase between conditions.

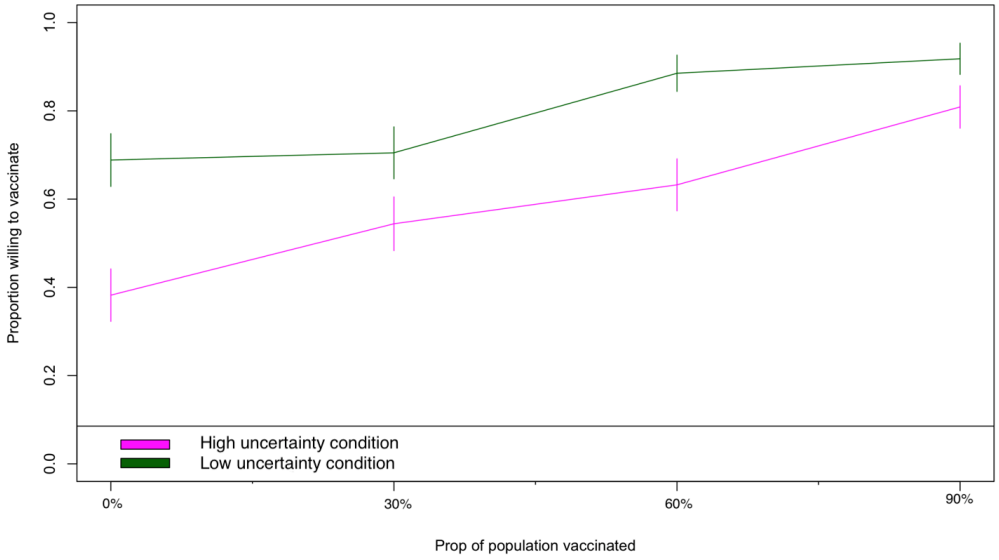


Figure W9. Proportion of participants willing to vaccinate for increasing population vaccination levels. Standard error bars are shown.

Author Accepted Manuscript

Table W29. Willingness to vaccinate is lower in the high than low uncertainty condition for 0% social proof nudge.

	Dependent Variable Vaccine choice (1 = yes, 0 = no)
High uncertainty condition	-1.273***
	(.376)
Social proof nudge 30%	.078
	(.136)
Social proof nudge 60%	1.250***
	(.349)
Social proof nudge 90%	1.623***
	(.428)
Social proof nudge 30% x high uncertainty condition	.579***
	(.246)
Social proof nudge 60% x high uncertainty condition	-.228
	(.416)
Social proof nudge 90% x high uncertainty condition	.299
	(.533)
Constant	.793***
	(.279)
Observations	516
Log Likelihood	-283.880
Akaike Inf. Crit.	583.760

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

Peer Review Version

We next look at the process measures. Specifically, whether the previous results can be explained by changes in perceived uncertainty of side effects, by social learning or feelings of having to conform with others.

Perceived uncertainty of side effects: A 2 x 4 mixed design ANOVA yielded a significant interaction effect between the population vaccination rate and type of vaccine ($F(3, 381) = 5.73$, $p < .001$, $\eta^2 = .043$), a significant main effect of the population vaccination rate ($F(3, 381) = 43.95$, $p < .001$, $\eta^2 = .257$) and a significant main effect of vaccine type ($F(1, 381) = 15.79$, $p = .001$, $\eta^2 = .077$). Figure W10 shows the results.

Author Accepted Manuscript

Pairwise comparisons indicated that in the high uncertainty condition, every increase in the population vaccination rate led to a significant decrease in perceived uncertainty (all p's < .006). However, in the low uncertainty condition, only the decrease when comparing the 30% versus 60% level was significant (p = .001). Further contrasts showed that at the 0% level, perceived uncertainty was higher in the high uncertainty than in the low uncertainty condition (p = .033), but not at higher levels of population vaccination rate. Thus, the perceived uncertainty of sides effects decreased more strongly with the increasing social proof nudge in the high uncertainty condition than in the low uncertainty condition.

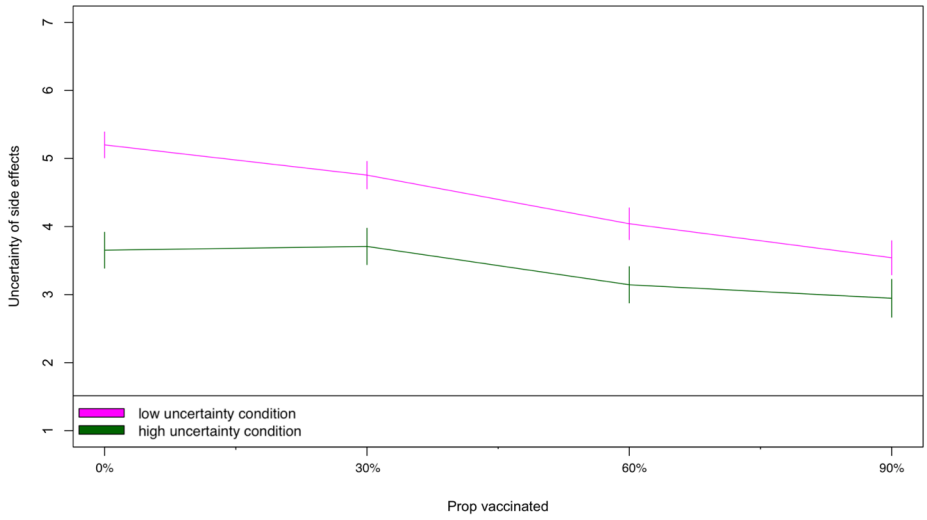


Figure W10. Perceived uncertainty across conditions.

Social learning: The results of a 2 x 4 mixed design ANOVA showed that the social proof nudge had a significant positive main effect on the measure of social learning ($F(3, 381) = 13.49$, $p < .001$, $\eta^2 = .096$) indicating that with increasing population vaccination rate, participants believed that others were more knowledgeable about the vaccination choice compared to themselves (contrasts: 0% vs 30%: p = .008; 30% vs. 60%: p = .032, 60% vs. 90%: p = .299). However, we found no main effect of the vaccine type or interaction effect between the social

Author Accepted Manuscript

proof nudge and vaccine type (all p's > .4). Thus, social learning is unlikely to explain the differential effect of social proof information on vaccine uptake. An OLS regression with social learning as dependent variable, social proof nudge, vaccine condition and their interaction as independent variables showed the same results.

Conformity: As normative pressure might differ depending on the vaccine choice, we ran separate analysis for affirmative versus opposing vaccine choices (69% of participants chose to vaccinate vs. 31% who chose not to vaccinate). Those who chose not to vaccinate felt more judged by others than those who chose to vaccinate ($\beta = -1.82$, $p < .001$). For participants who chose *not* to vaccinate, we find the following pattern. The results of a 2 x 4 mixed design ANOVA showed that the social proof nudge had a significant positive main effect on the measure of conformity ($F(3, 91) = 4.85$, $p = .003$, $\eta^2 = .137$) indicating that with increasing population vaccination rate, participants felt more judged by others (contrasts: 0% vs. 30%: $p = .716$; 30% vs. 60%: $p = .039$, 60% vs. 90%: $p = .052$). However, we found no main effect of the vaccine type or interaction between the social proof nudge and the vaccine type (all p's > .7). This indicates that those who refused to vaccinate generally felt higher pressure to conform irrespective of the vaccine type, and this pressure increased with an increasing population vaccination rate. For participants who *chose* to vaccinate, we find a different pattern. They felt more judged in the high uncertainty condition than in the low uncertainty condition ($F(1, 238) = 12.11$, $p < .001$, $\eta^2 = .099$). The social proof nudge decreased feelings of being judged for choosing to vaccinate ($F(3, 238) = 42.28$, $p < .001$, $\eta^2 = .347$). Nevertheless, there was no interaction between the vaccine type and the social proof nudge ($p = .656$). Therefore, conformity is unlikely to fully explain the effect of herd behavior information on vaccine uptake.

Peer Review Version

Author Accepted Manuscript

Mediation analysis: A mediation analysis further confirmed the role of perceived uncertainty as the most plausible mechanism explaining the relationship between the social proof nudge and the vaccine type (Hayes' PROCESS macro, Model 4 with 5,000 bootstrap samples; Hayes 2013). In the high uncertainty condition, the social proof nudge lowered the perceived uncertainty of side effects (β = -.014, SE = .003, 95% CI = [-.019, -.009], $p < .001$). Higher perceived uncertainty decreased the odds of choosing to vaccinate (Logit regression, β = -.437, SE = .056, 95% CI = [-.547, -.327], $p < .001$). The perceived uncertainty mediated the relationship between vaccine type and choosing to vaccinate (Indirect effect: β = -.006, SE = .001, 95% CI = [.004, .009].

Social learning and conformity measures did not mediate the relationship between vaccine type and choosing to vaccinate in the high uncertainty condition (social learning: Indirect effect: β = .0002, SE = .001, 95% CI = [-.002, .002], conformity: Indirect effect: β = .002, SE = .001, 95% CI = [-.0003, .0056]. As expected, in the low uncertainty condition we found that perceived uncertainty did not mediate the relationship between vaccine type and vaccine choice (see Figure W11 for the mediation model in high uncertainty condition).

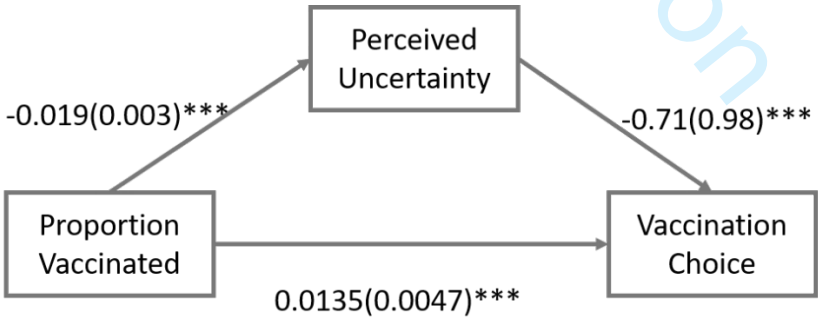


Figure W11. Mediation model in the high uncertainty vaccine condition.

Peer Review Version

Author Accepted Manuscript

Supplementary Study 4 – The Role of Risk Aversion

The aim of this study was to investigate risk preferences. Based on the model, we hypothesized that highly risk averse consumers who overweight small probabilities of severe outcomes, would show stronger aversion to a new technology vaccine; further, the social proof nudge would be more effective among those in reducing new technology aversion (H3b). To test this, we measured risk aversion using methods commonly employed in health economics. We also include a semi-consequential outcome measure (sign-up to a mailing list).

Methodology

The vaccine stimuli and experimental design was the same as previously apart from the following changes. Instead of manipulating the vaccine technology between-subjects, participants were shown both vaccine types and choose between them on a 7-point Likert scale. If they selected values left (right) of the midpoint, they preferred the traditional (new) technology; if they selected the mid-point, they were indifferent.[2] Hence, we obtained a direct measure of aversion to the new technology vaccine. The distance from the scale midpoint indicates the strength of preference. We did not collapse the data, but instead used the full continuous scale as dependent variable to capture the strength of preference between new and traditional technology. Participants were randomly assigned to two between-subjects conditions for the social proof nudge: 0% vs. 60% population vaccination rate.

As a semi-consequential outcome, we asked participants whether they wanted to sign-up to a mailing list for information about the logistics of when and where they could receive a particular type of vaccine (response options: no, sign-up for new technology vaccine, sign-up for traditional technology vaccine).

[2]After indicating their preference, participants could also indicate if they were unwilling to receive any vaccine type. Including or excluding these participants (n = 24), did not change our results.

Peer Review Version

Author Accepted Manuscript

We included a single-item measure of risk aversion 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 higher willingness to take risks (less risk aversion).

To test our model prediction (H3b) that overweighting of small probabilities of extreme losses leads to larger aversion to new technology vaccines, we elicited risk preferences for small probabilities of health losses. The elicitation method was adapted based on literature in health economics (Attema, L'Haridon, and van de Kuilen 2019). Participants read a scenario in which they had been diagnosed with a disease that was expected to reduce 20 years from their life. There were two treatments that were equally effective on average costing $10,000. Treatment A had a 1% chance of losing 10 years and a 99% chance of losing 5 years; Treatment B had a 1% chance of losing 15 years and a 99% chance of losing 4 years and 10 months. Although the expected value of both treatments is equal, treatment B with extreme outcomes is riskier than Treatment A. We asked how much they were willing to pay to switch from Treatment B (the default) to Treatment A (scale: $0–$10,000).

Peer Review Version

Sample

We recruited N = 165 US adults (M_{age} = 41.76, SD = 12.39, range: 20 - 77 years, 60.61% male) via from Amazon Mechanical Turk using CloudResearch (Litman, Robinson, and Abberbock 2017).

Results

The average of the vaccine preference rating was lower than the scale midpoint (M = 3.61, SD = 2.05, t(164) = -2.42, p = .016, d = .19), indicating aversion to the new technology vaccine.

Author Accepted Manuscript

The social proof nudge significantly reduced this aversion. At the 0% population vaccination rate, participants had a stronger preference for the traditional technology vaccine (M = 3.07, SD = 1.87) than at 60% (M = 4.14, SD = 2.09, t(163) = -3.46, $p < 001$, d = .53). At the 60% population vaccination rate, the rating was not different from the scale midpoint ($p = .53$).

A similar result emerges for the semi-consequential outcome, sign-up to a mailing list. In both conditions, a about half did not want to sign up (0% population vaccination rate: 48.78%, 60% population vaccination rate: 51.81%). Among those willing to sign up, preferences switched with the increasing population vaccination rate ($chi^2(2) = 11.16$, $p = .004$). At the 0% population vaccination rate, 17.07% signed up for the new technology vaccine versus 34.15% for the traditional technology vaccines (exact binomial test: $p = .043$). At the 60% population vaccination rate 33.73% signed up for the new technology vaccine versus 14.46% for the traditional technology vaccine (exact binomial test: $p = .016$). Thus, the social proof nudge was effective in reducing aversion to the new technology vaccine.

Next, we analyzed to what extent risk aversion was associated with vaccine preferences, using linear regression. As predicted, higher self-rated risk taking was associated with a higher preference for the new over the traditional technology vaccine (b = 0.153, $p = .015$, table W30).

For risk aversion measured for small probabilities of a health loss, an interaction effect with the social proof nudge emerged (b = .034, $p = .006$), consistent with the model's prediction (table W31). The interaction effect indicates that the social proof nudge was more effective among those with higher risk aversion (i.e., those who wanted to avoid a small probability of a health loss) in reducing new technology aversion. This indicates that due to the social proof nudge, risk-averse participants felt more confident about the new technology and tended to be more willing to adopt.

Peer Review Version

Author Accepted Manuscript

These results confirm H3b. There was also a main effect of risk aversion. Risk averse participants were more averse to the new technology vaccine.

Table W30. Willingness to take risk is associated with a higher preference for the new (compared to traditional) technology vaccine.

	Dependent Variable: Vaccine preference (higher values indicate less aversion to new technology)
Social proof nudge 60%	1.085
	(.307)***
Willingness to take risks (self-rated)	.153
	(.062)**
Age	.017
	(.013)
Female	-.040
	(.321)
Income	.079
	(.120)
White/Caucasian	.801**
	(.353)
Constant	.907
	(.704)
Observations	161
R-squared	.156
Adj. R-squared	.1229
Residual Std. Error	574.148 (df = 154)
F-test	4.738 (df = 6, 154)***

Note. *** $p < .01$, ** $p < .05$, * $p < .1$

Peer Review Version

Author Accepted Manuscript

Table W31. Risk aversion interacts with social proof nudge to predict vaccine preference.

	Dependent Variable: Vaccine preference (higher values indicate less aversion to new technology)
Social Proof Nudge - 60%	.445
	(.374)
Risk aversion small probabilities	-.016*
	(.008)
Social proof nudge 60% x Risk Aversion	.034***
	(.012)
Age	.013
	(.013)
Female	.037
	(.322)
Income	.124
	(.118)
White/Caucasian	.816**
	(.352)
Constant	1.881***
	(.648)
Observations	161
R-squared	.165
Adj. R-squared	.127
Residual Std. Error	567.692 (df = 153)
F-test	4.33*** (df = 7, 153)

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

Peer Review Version

Author Accepted Manuscript

Supplementary Study 5 – Generalizability Pilot

The goal was to test the generalizability of our findings in other domains. Specifically, we investigated new technology aversion in two areas of innovation: energy (lithium battery cars, hydrogen heating) and cybersecurity (voice authentication). The stimuli were created with information from news articles on innovative products. Participants were randomly assigned to one of two different between-subjects conditions: control condition without information about others' behavior vs. social proof nudge condition with information about others' behavior.

Sample

A sample of 120 US residents (45.83% females, M_{age} = 43.22, SD = 12.41, range: 22 - 77 years) was recruited via CloudResearch using MTurk participants to ensure high data quality.

Methodology

Participants were informed that they would evaluate different products related to technology in a five-minute survey. After providing consent, participants evaluated three products in randomized order. These products were described in terms of benefits and risks (see descriptions in Table W32). In the social proof nudge condition, participants also read information about others' behavior (see Table W32). They provided their product evaluation on a slider scale from 0 to 100 (0 = preference for the new technology, 50 = indifferent, 100 = preference for the traditional technology). In addition, on a new page, we measured the perceived uncertainty of the new technology (e.g., "*Please rate how risky you think this LITHIUM technology is*". Scale: 1 = less risky, 7 = more risky than traditional technology). After evaluating all three products, participants answered questions about demographics (age, gender, income, education, ethnicity, and occupation).

Peer Review Version

Author Accepted Manuscript

Table W32. Description of stimuli used in supplementary study 5.

	Energy domain		Cybersecurity domain
	Lithium-battery car	**Hydrogen heating system**	**Voice Authentication**
Benefits	Electric cars are better for the environment and save consumers money in the long run - recent reports indicate as much as $1,000 a year. Lithium car batteries are superior to alternatives in the field in many ways, including price and efficiency. The most important environmental benefit of lithium-based batteries is that vehicles that use them spend less carbon and add less to the carbon footprint than any other traditional source of power for motorized vehicles.	Hydrogen boilers are currently being tested to see if they can be used to replace gas for greener heated homes. The main benefit of hydrogen is that produces no carbon dioxide at the point of use and can be manufactured from either water using electricity as a renewable energy source, or from natural gas accompanied by carbon capture and storage. A typical three-bedroom home is said to be able to save $3,400 in ten years by using this instead of a gas boiler.	Voice authentication is a biometric method of speaker recognition based on measuring the distinctions in different voices to uniquely identify users. Instead of a password, which might be forgotten or not strong enough to assure security, voice recognition allows people to use their voices themselves as passwords. Banks have been a big adopter of voice authentication technology. They can verify customers within the first few seconds of calling.
Risks	A lithium-ion battery short circuits can happen from causes including a battery cell puncture or heat exposure during a car accident. These batteries can even spontaneously combust because of silicon expansion, dendrite formation or other reasons. In that case, the battery produces a spontaneous fireball explosion that heats to 1300°F in milliseconds.	Hydrogen is more flammable and lighter and is yet to have been used on the grid to heat the country. It is possible that hydrogen boilers cause explosions.	The current state of voice biometrics is still being improved. Voice samples from something like a YouTube video can be accepted as approved speech patterns. Hackers have been able to bury malicious commands in white noise to control voice-enabled devices.
Social proof nudge	In some US states, lithium battery car sales represent 18% of all car sales.	In some communities, up to 60% of houses are heated by using hydrogen systems.	At some banks, around 70% of customers have used the voice authentication system.
Dependent variable	Would you want your car to run on a lithium battery?	Would you heat your home with hydrogen?	Would you enroll in a voice authentication program with your bank?

Peer Review Version

Author Accepted Manuscript

Results

We found aversion to new technology for all three products. The means for each product were significantly above the scale mid-point indicating a preference for the traditional technology. The social proof nudge reduced this aversion and the perceived uncertainty for the energy domain items (lithium battery car and hydrogen heating system) but not for the cybersecurity item (voice authentication). Results are shown in Figure W12a and W12b.

We averaged the product evaluation and perceived uncertainty ratings for the energy domain and performed a mediation with 5,000 bootstrap samples. The social proof nudge significantly lowered perceived uncertainty (β = -.599, SE = .215, 95% CI = [-1.02, -.177], p = .005). Higher perceived uncertainty increased preference for the traditional technology (i.e., decreased new technology aversion, β = 13.44, SE = 1.45, 95% CI = [10.58, 16.30], p < .001). Perceived uncertainty mediated the relationship between the social proof nudge and new technology aversion (Indirect effect: β = -8.05, SE = 3.16, 95% CI = [-14.26, -1.85], p < .011). Thus, the reduction in perceived uncertainty mediated the relationship between the social proof nudge and technology aversion, generalizing our findings from vaccines to energy technology.

While we find new technology aversion in the cybersecurity domain, the social proof nudge was not effective in reducing perceived uncertainty, and in reducing new technology aversion. We speculate that this might be because the cybersecurity context 'only' contains a risk of economic losses while both the vaccine and the energy context contained a potential health loss.

Peer Review Version

Author Accepted Manuscript

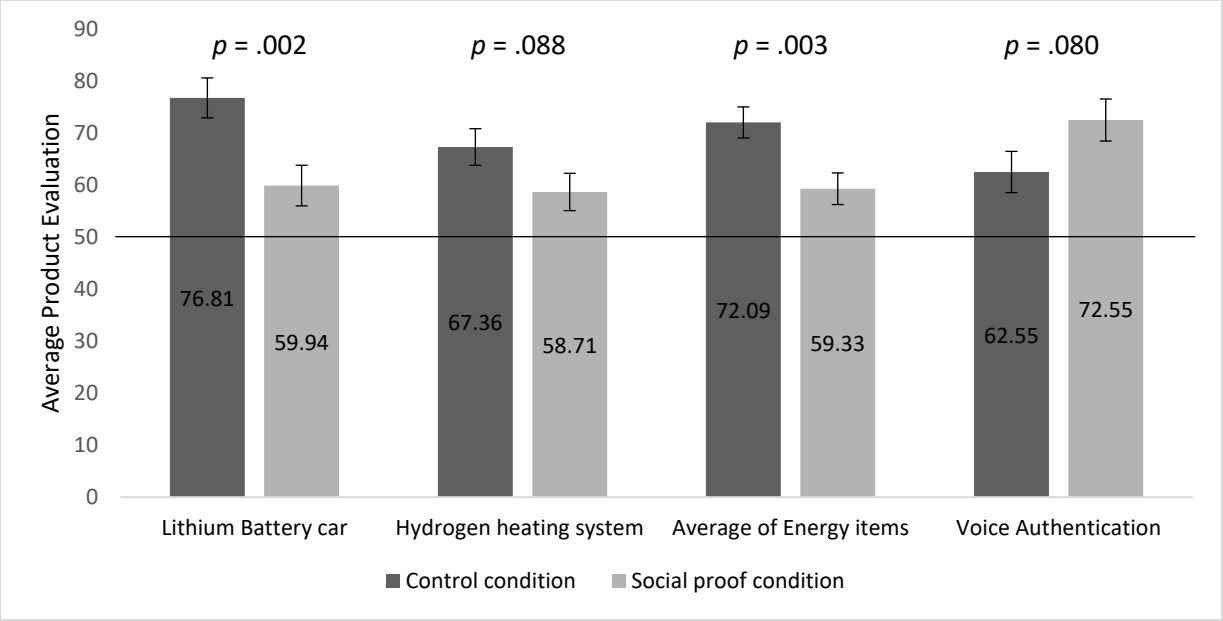


Figure W12a. Average product evaluations across products and conditions (the line at 50 marks the indifference point; higher ratings indicate aversion to new technology; standard errors bars are shown).

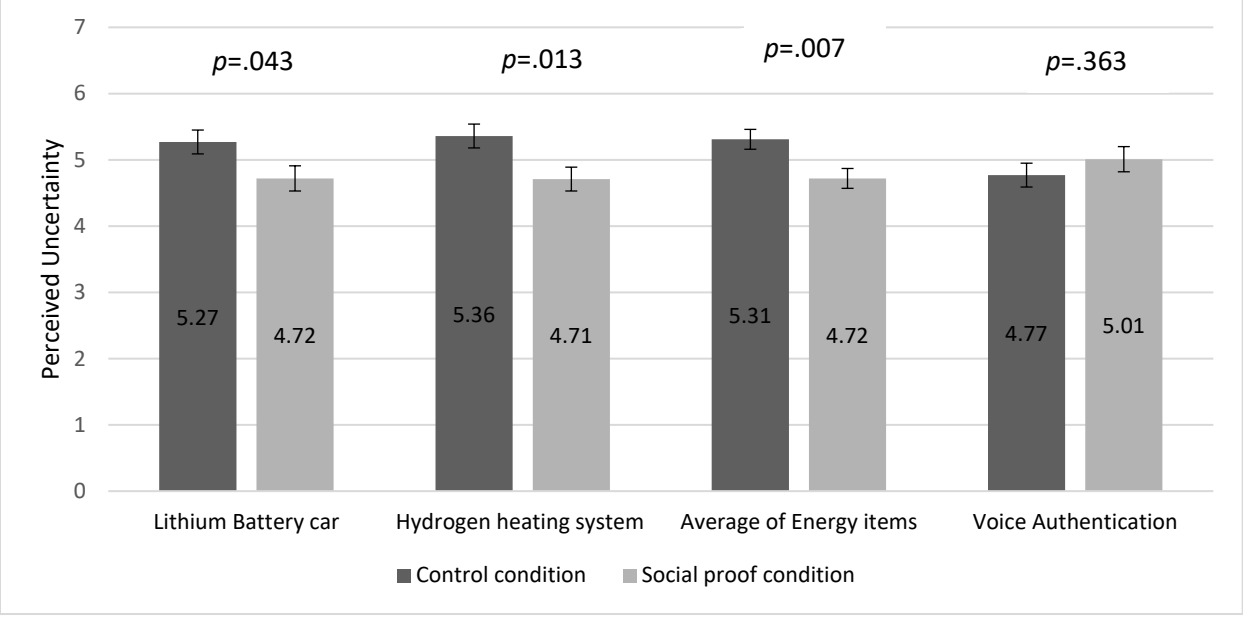


Figure W12b. Average perceived uncertainty across product domains and conditions (higher ratings indicate higher perceived uncertainty, standard errors bars are shown).

Author Accepted Manuscript

References

Attema, Arthur E., Olivier L'Haridon, and Gijs van de Kuilen (2019), "Measuring multivariate risk preferences in the health domain," *Journal of Health Economics*, 64, 15–24.

Blaisdell, Laura L., Caitlin Gutheil, Norbert A. M. Hootsmans, and Paul K. J. Han (2016), "Unknown Risks: Parental Hesitation about Vaccination," *Medical Decision Making*, 36 (4), 479–89.

Decker, Simon and Hendrik Schmitz (2016), "Health shocks and risk aversion," *Journal of Health Economics*, 50, 156–70.

Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G. Wagner (2011), "Individual risk attitudes: Measurement, Determinants, and behavioral consequences," *Journal of the European Economic Association*, 9 (3), 522–50.

Dubov, Alex (2015), "Ethical persuasion: the rhetoric of communication in critical care," *Journal of Evaluation in Clinical Practice*, 21 (3), 496–502.

Eeckhoudt, Louis and Christian Gollier (2005), "The Impact of Prudence on Optimal Prevention," *Economic Theory*, 26 (4), 989–94.

Han, Paul K. J., Brian J. Zikmund-Fisher, Christine W. Duarte, Megan Knaus, Adam Black, Aaron M. Scherer, and Angela Fagerlin (2018), "Communication of Scientific Uncertainty about a Novel Pandemic Health Threat: Ambiguity Aversion and Its Mechanisms," *Journal of health communication*, 23 (5), 435–44.

Hayes, Andrew F (2013), *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach.* Guilford Press.

Litman, Leib, Jonathan Robinson, and Tzvi Abberbock (2017), "TurkPrime.com: A versatile crowdsourcing data acquisition platform for the behavioral sciences," *Behavior Research Methods*, 49 (2), 433–42.

Ritov, Ilana and Jonathan Baron (1990), "Reluctance to vaccinate: Omission bias and ambiguity," *Journal of Behavioral Decision Making*, 3 (4), 263–77.

Rothschild, Michael and Joseph E. Stiglitz (1970), "Increasing risk: I. A definition," *Journal of Economic Theory*, 2 (3), 225-243.

Tversky, Amos and Daniel Kahneman (1992), "Advances in prospect theory: Cumulative representation of uncertainty," *Journal of Risk and Uncertainty*, 5, 297–323.

Wakker, Peter and Daniel Deneffe (1996), "Eliciting von Neumann-Morgenstern Utilities When Probabilities are Distorted or Unknown," *Management Science*, 42 (8), 1131–50.

Peer Review Version