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Support for deepfake regulation: The role of third-person perception, trust, and risk

Unterstützung für Deepfake-Regulierung: Die Rolle von Third-Person-Perception, Vertrauen und Risiko

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Abstract: Like other emerging technologies, deepfakes present both risks and benefits to society. Due to harmful applications such as disinformation and non-consensual pornography, calls for their regulation have increased recently. However, little is known about public support for deepfake regulation and the factors related to it. This study addresses this gap through a pre-registered online survey (n = 1,361) conducted in Switzerland, where citizens can influence political regulation through direct democratic instruments, such as referendums. Our findings reveal a strong third-person perception, as people believe that deepfakes affect others more than themselves (*Cohen's d* = 0.77). This presumed effect on others is a weak but significant predictor of support for regulation (β = 0.07). However, we do not find evidence for the second-person effect – the idea that individuals who perceive deepfakes as highly influential on both themselves and others are more likely to support regulation. However, an exploratory analysis indicates a potential second-person effect among females, who are specifically affected by deepfakes; a result which must be further explored and replicated. Additionally, we find that higher perceived risk and greater trust in institutions are positively associated with support for deepfake regulation.

Keywords: Deepfake technology, regulation, third-person effect, second-person effect, risk perception, trust

Zusammenfassung: Wie andere aufkommende Technologien bringen Deepfakes sowohl Risiken als auch Vorteile für die Gesellschaft mit sich. Aufgrund schädlicher Anwendungen wie Desinformation und nicht einvernehmlicher Pornografie sind die Forderungen nach einer Regulierung von Deepfake-Technologie jüngst gestiegen. Allerdings ist wenig darüber bekannt, inwieweit die Öffentlichkeit eine Regulierung von Deepfakes unterstützt und welche Faktoren dabei eine Rolle spielen. Diese Studie adressiert diese Forschungslücke mit einer präregistrierten Online-Befragung (n = 1.361) in der Schweiz, einem Land, in dem Bürgerinnen und Bürger durch direktdemokratische Instrumente wie Referenden Einfluss auf die politische Regulierung nehmen können. Unsere Ergebnisse bestätigen die Third-Person-Perception: Menschen glauben, dass Deepfakes andere stärker beeinflussen als sich selbst (*Cohen's d* = 0,77). Dieser vermutete Effekt auf andere ist ein schwacher, aber signifikanter Prädiktor für die Unterstützung einer Regulierung (β = 0,07). Allerdings finden wir keine Hinweise auf den Second-Person-Effekt–die Annahme, dass Personen, die Deepfakes sowohl bei anderen als auch bei sich selbst als besonders einflussreich wah-

rnehmen, eine stärkere Unterstützung für Regulierungsmaßnahmen zeigen. Eine explorative Analyse weist allerdings auf einen potenziellen Second-Person-Effekt bei Frauen hin, die besonders von Deepfakes betroffen sind; dieses Ergebnis muss weiter untersucht und repliziert werden. Darüber hinaus stellen wir fest, dass eine höhere Risikowahrnehmung sowie ein größeres Vertrauen in Institutionen positiv mit der Unterstützung für eine Regulierung von Deepfakes zusammenhängen.

Schlagwörter: Deepfake-Technologie, Regulierung, Third-Person-Effekt, Second-Person-Effekt, Risikowahrnehmung, Vertrauen

1. Introduction

Emerging technologies usually come with benefits and risks for society. How and if a technology can establish itself in society depends on how individuals perceive its risks and benefits (Gardner & Gould, 1989; Lima et al., 2005; Slovic et al., 1982). A common approach to coping with the risks of technology is regulation by the state or self-regulation by technology providers. Calls for regulation are often articulated in the public by citizens, journalists, politicians, or non-governmental organizations when the risk of a technology is perceived as outweighing its benefits (Nguyen, 2023). In the field of communication technology, regulatory initiatives have targeted the internet, social media platforms, and AI – often in response to concerns about problematic content, such as disinformation, pornography, or potential negative effects on users, including privacy issues, well-being, violence, and addiction (de Ruiter, 2021; Kim, 2025; Paradise & Sullivan, 2012; Yu et al., 2023).

While deepfake technology has beneficial applications in certain industries and for personal recreation (Bendahan Bitton et al., 2024; Rauchfleisch et al., 2025), it also poses significant risks, particularly in relation to disinformation (Godulla et al., 2021; Hameleers et al., 2022; Vaccari & Chadwick, 2020) and pornography (de Ruiter, 2021). To mitigate these risks, technological detection methods, (digital) media literacy initiatives, as well as regulation by the state or the industry itself, are currently being discussed (Birrer & Just, 2024). However, regulating deepfakes is legally complex, may create economic disadvantages, and is often perceived as a restriction on freedom of speech (Godulla et al., 2021).

In democracies, public acceptance of regulations is crucial, particularly in Switzerland, where referendums can be held on proposed regulations. However, little is known about citizens' support for regulating deepfake technology and the factors related to such support. From studies on disinformation, we know that the perceived negative effects of disinformation are positively related to support for the regulation of content and platforms (Jungherr & Rauchfleisch, 2024). The literature also shows third-person effects related to regulation of technology, as the perception of others' high vulnerability to disinformation or other harmful content is positively associated with support for regulation (Chen et al., 2023; Chung & Wihbey, 2024; Kim, 2025; Riedl et al., 2022).

Our pre-registered online study conducted in Switzerland addresses this gap by drawing on third-person effect literature (Baek et al., 2019; Davison, 1983; Gunther & Storey, 2003).[1] The study shows that people believe deepfakes have a greater influence on others than on

1 Preregistration and full list of hypotheses available at https://aspredicted.org/s2gt-7rwr.pdf

themselves (perceptual third-person effect) and that the perceived effect on others is positively related to support for deepfake regulation. An additional exploratory analysis indicates that gender plays a role. While the presumed effect on others explains support for regulation among male citizens, we observed a potential second-person effect for female citizens, as those who perceive deepfakes as influential on themselves and others show even stronger regulatory support. Furthermore, the study indicates a positive association between support for deepfake regulation and both trust in institutions and perceived risks associated with deepfakes.

2. Conceptual framework

One way to mitigate the risks posed by technology is through regulation. Deepfakes, often associated with disinformation, pornography, and criminal activity in public discourse in Switzerland (Rauchfleisch et al., 2025) and other countries (Gosse & Burkell, 2020; Yadlin-Segal & Oppenheim, 2021), have prompted calls for state-led regulation or self-regulation by platforms. Although few specific laws targeting deepfakes currently exist, they are often addressed within broader regulatory frameworks concerning AI, disinformation, and privacy. In Europe, for instance, providers and moderators of deepfake technology are subject to the Digital Services Act (DSA) and the AI Act. The AI Act requires systems that generate and manipulate images to meet minimal transparency standards (Karaboga et al., 2024). Switzerland recently rejected a specific regulation regarding deepfakes (Swissinfo, 2025), but existing laws, such as criminal law and privacy rights, can still apply to cases involving deepfakes (Thouvenin et al., 2023). This indicates that regulating technologies like deepfakes is a continuum that encompasses multiple frameworks.

2.1 Third-person effect and behavioral second-person effect

The extent to which emerging technologies are regulated depends mainly on the risks and benefits associated with them (Slovic et al., 1982). In the case of deepfakes, their potential impact on public opinion, particularly as a tool for disinformation, is a central concern. Research on the perceived negative effects of communication technology like deepfakes, social media platforms, or games suggests a third-person effect (Davison, 1983), where individuals tend to view the harms as greater for unknown others than for themselves (Ahmed, 2023; Chen et al., 2023; Paradise & Sullivan, 2012; Riedl et al., 2022; Yu et al., 2023), with further notable differences between close and distant others (Altay & Acerbi, 2024; Corbu et al., 2020). Initially developed as a primarily perceptual phenomenon by Davison (1983), the concept was later expanded to include a behavioral dimension. Such extensions suggest the existence of an "influence of presumed influence" (Gunther & Storey, 2003, p. 199), which leads individuals to adjust their behavior based on the belief that others are influenced by the media (Baek et al., 2019).

To date, few studies have analyzed third-person perceptions of the influence of deepfakes. A noteworthy exception is the study by Ahmed (2023), which is based on the third-person perception framework and demonstrates that individuals in the US and Singapore perceive deepfakes as influencing others more than themselves. Many studies have demonstrated the third-person effect for disinformation: Individuals perceive themselves as more capable of detecting disinformation (Corbu et al., 2020) and less vulnerable to it (Jang & Kim, 2018; Kim, 2025; Liu & Huang, 2020) than others.

The third-person effect is positively related to higher support for regulating communication technologies. Chung and Wihbey (2024) show that presumed media effects on others are related to support for governmental platform regulation as well as self-regulation (i.e., content moderation) in the US, the UK, and South Korea. Thereby, the perceived ability of others to spot misinformation acts as an antecedent of the third-person effect. Similarly, Kim (2025) showed a positive relation between third-person perception of COVID-related disinformation and support for regulating such content. Riedl et al. (2022) identified the third-person perception for perceived effects of social media content on others and platform moderation. However, not all studies lend support to this relationship (Chen et al., 2023). Interestingly, Jang and Kim (2018) demonstrate in their US-based study that the third-person perception of disinformation is positively related to support for media literacy interventions, but not for regulatory approaches by the state or platforms.

In the context of fake news and platform regulation, prior research in some cases supports a second-person effect instead of a third-person effect for the behavioral hypothesis. For example, Riedl et al. (2022) observe a behavioral second-person effect, meaning that people who perceive effects of social media content as high on both themselves and others support extended content moderation but not stronger platform regulation through the state. Similarly, Baek et al. (2019) also identify a second-person effect for the presumed effect of fake news and support for regulation. In our study, we first assume, as a perceptual third-person hypothesis, a difference between the presumed effect of deepfakes on self and others:

> *H1: Individuals will presume a greater deepfake effect on "others" than on the "self".*

The presumed effect on others alone might explain support for regulation. Here, we follow the literature on the "influence of presumed influence" (Gunther & Storey, 2003, p. 199). The following hypothesis can also serve as an alternative explanation if we do not find support for a second-person effect (H3) where the association between the presumed effect on others and support for regulation is moderated by the presumed effect on oneself (Baek et al., 2019).

> *H2: Individuals' presumed deepfake effect on "others" is positively related to their support for the regulation of deepfakes.*

Prior research in the context of online communication (Riedl et al., 2022) and disinformation (Baek et al., 2019) indicated a second-person effect. We also assume, as a behavioral hypothesis, a second-person effect in the context of deepfakes, which would be supported by a significant interaction effect between the presumed effect on others and the self. In contrast, the third-person effect suggests that the issue is perceived primarily as a problem affecting others, rather than oneself. If the interaction is not significant, a significant positive estimate for presumed effect on others and a negative presumed effect on self would support a strict third-person effect. Only a significant negative estimate for presumed effect on others would support the less strict influence of presumed influence as stated in H2:

> *H3: Individuals with both high presumed deepfake effects on "others" and "self" will show stronger support for the regulation of deepfakes.*

2.2 Trust in institutions

In democracies, regulation is often at least partially delegated to the state. Together with technology providers and experts, state regulators develop frameworks for technology regulation. The delegation of power and responsibility for regulation to a third party requires trust (Six, 2013; Verhoest et al., 2025). However, "in regulatory regimes, the provision of third-party trust is only useful as long as citizens trust the third party" (Verhoest et al., 2025, p. 365). In his theory of justified public trust in regulation, Wolf (2021) highlights that to be trustworthy a regulatory regime must "fairly and effectively manage risk, must be 'science based' in the relevant sense, and must in addition be truthful, transparent, and responsive to public input" (p. 29). We argue that two central institutions ensuring such trustworthy regulatory frameworks are politics and journalism. Politics is the primary actor in drafting, developing, and implementing state-led regulatory frameworks. In an experimental study by PytlikZillig et al. (2017), the participants' trust in water regulatory institutions was positively related to their general trust in government. In a study encompassing 33 European countries, Marien and Hooghe (2011) demonstrate that low trust in the institutions of the political system is associated with a higher acceptance of illegal behavior, such as tax fraud, indicating that individuals are less likely to follow governmental regulations. Journalism, in its role as a watchdog, critically observes the regulatory process and detects weaknesses and undesirable developments (Kalogeropoulos et al., 2022). Therefore, we expect a positive relation between trust in institutions and support for deepfake regulation:

> *H4: Individuals with higher trust in institutions will show stronger support for the regulation of deepfakes.*

2.3 Risk perceptions

New technology always comes with potential risks and benefits for society. The implementation of technology, and how it can be utilized, depends on how these risks and opportunities are perceived by members of a society (Gardner & Gould, 1989; Lima et al., 2005). Calls for state-led regulation of technology usually emerge when individuals or groups perceive the risks as outweighing the benefits of a technology. The perception of risks also depends on the field of application of a technology, as possible benefits may occur in one field and risks might be identified in another. Regarding deepfakes, the risks to politics might be perceived as more severe than those related to the economy, making support for regulation more likely when the risks to politics are regarded as high. Research on disinformation has shown that higher problem perception increases support for regulating online environments (Jungherr & Rauchfleisch, 2024). Considering differences in application fields, we therefore hypothesize that higher risk perceptions will be associated with stronger support for regulating deepfakes.

> *H5: Individuals with higher risk perception of deepfakes for a) politics, b) the media, c) the economy, and d) the "self" will show stronger support for the regulation of deepfakes.*

3. Methods

Our pre-registered study was approved by the ethics committee of the Faculty of Arts and Sciences of the University of Zurich. We used an online panel (Respondi-Bilendi) for our survey, which was conducted in September 2023 (N = 1,361 participants). Participants are individuals residing in Switzerland who are 16 years of age or older. The sample includes participants from both the French and German language regions. Before we began the survey, we ensured that we had sufficient power for our statistical tests. For a sample of 1,200, we had a power of more than 0.9 for all our statistical tests (see Appendix C for more details). The surveys were programmed and administered in both languages using Unipark software. Because the natural fallout in our sample resulted in some age groups having a disproportionate number of female respondents, we computed survey weights based on Swiss population data. In the main paper, we present the model using weighted data (see Appendix D.2.1 for the model with unweighted data).

3.1 Measures

The dependent variable, *support for regulation of deepfakes*, was measured with four items covering support for (1) a general ban of deepfakes, (2) a regulatory framework for prohibiting deepfakes, (3) state-led regulation and (4) self-regulation of deepfakes by platforms (M = 5.10; SD = 1.45; α = .77). We used the items from Baek et al.'s (2019) study and adapted them to the context of our study (overview of the main measures is provided in Appendix B.1).

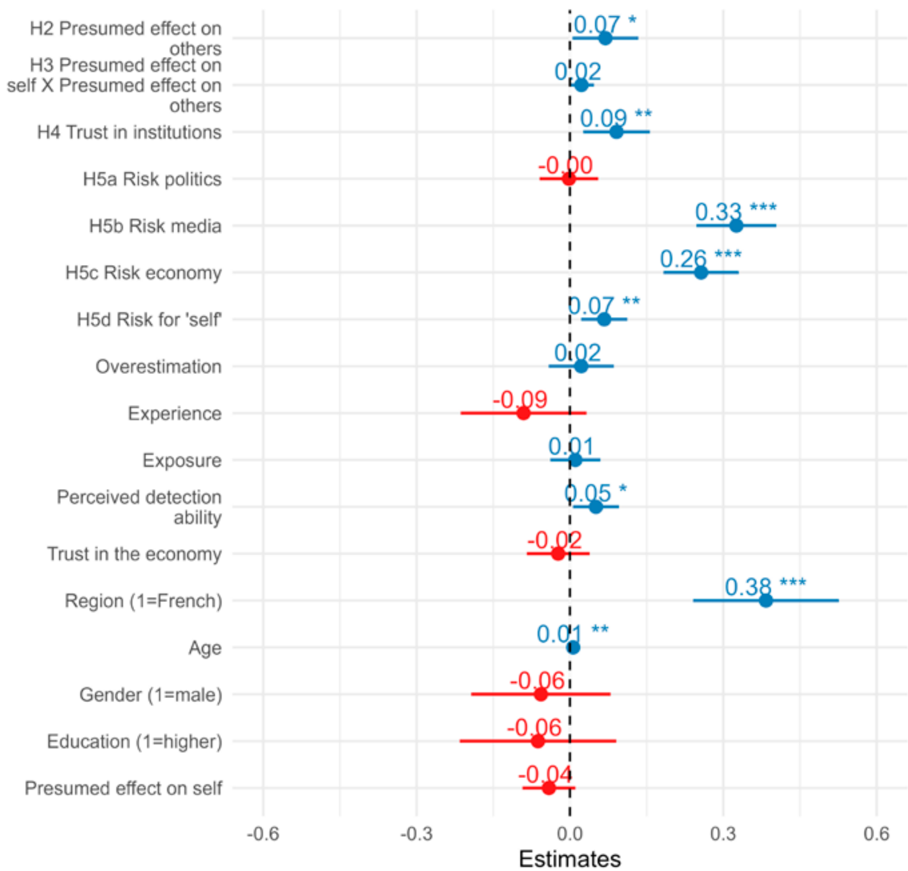
Presumed effects of deepfakes on self and others were measured with two single items by asking participants to estimate how deepfakes influence their own opinions [M = 3.53; SD = 1.70] and the opinions of the Swiss population [M = 4.70; SD = 1.45]. *Trust in institutions* was measured using two items that covered trust in political institutions and journalism (M = 3.71; SD = 1.31; α = .74). We assessed risk perceptions for the different application fields using two items each. We included risks for politics (M = 4.98; SD = 1.64; α = .89), journalism (M = 5.81; SD = 1.20; α = .70), the economy (M = 4.88; SD = 1.46; α = .81) as well as individual risks, for instance, privacy-related concerns (M = 4.10; SD = 1.83; α = 0.73).

As pre-registered we also included variables for *overestimation of deepfakes*, *prior experience with deepfakes*, *prior exposure to deepfakes*, the *perceived ability to detect deepfakes*, *trust in the economy*, *gender*, *age*, and *educational attainment* (for a complete overview of measures, see Appendix B.1). As an analytical strategy, we follow Baek et al.'s (2019) recommendation and test the presumed effect on self and others as an interaction term in the regression model. This approach allows us to clearly identify a first-person effect, a second-person effect (H3: significant interaction term), a strict third-person effect (significant positive presumed effect on others and negative presumed effect on self), and the less strict presumed effects on others (H2: significant positive presumed effect on others; Gunther & Storey, 2003). Presumed effects on self and others were both mean-centered before estimating the model.

4. Results

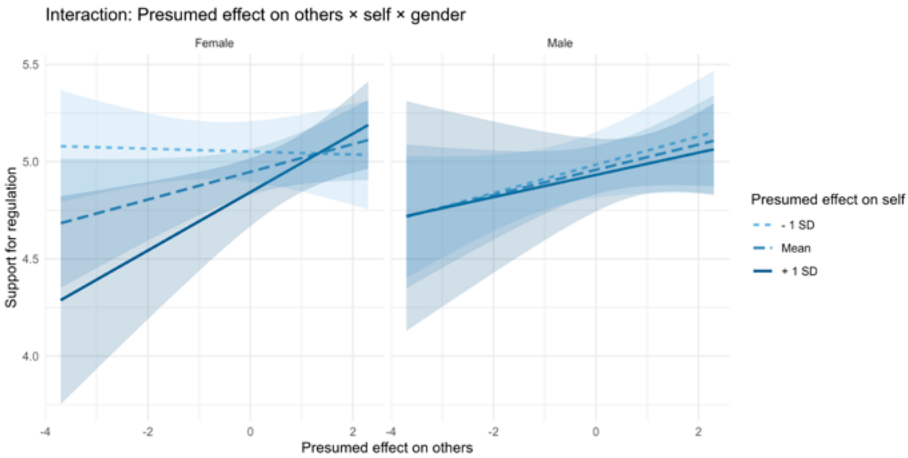
Our data support the perceptual hypothesis (H1), as people perceive deepfakes to have a stronger effect on others than on themselves. A paired-samples t-test ($t(1360) = -28.54$, $p < .001$; *Cohen's d* = 0.77) indicated a significant difference between the two variables, with the presumed effect on self ($M = 3.53$, $SD = 1.70$) being over one scale point lower than the presumed effect on others ($M = 4.70$, $SD = 1.45$). We also find support for H2 as a higher presumed effect on others is positively associated with stronger support for regulation of deepfakes ($b = 0.07$, 95% CI [0.01,0.13], $p = .035$, $\beta = 0.07$; see Figure 1 for all estimates and Appendix D.1.1 for the complete model). However, we do not find support for H3. While the interaction effect is positive, which would be an indicator for a second-person effect, the estimate is not significant ($b = 0.02$, 95% CI [-0.00,0.05], $p = .074$). We find support for H4 as higher trust in institutions is positively

Figure 1. All estimates from the regression model with 95%-CIs



Note. Estimates are shown with significance level: *$p < .05$, **$p < .01$, ***$p < .001$.

Figure 2. Interaction effect between presumed effect on others, presumed effect on self, and gender.



related to higher support for regulation (b = 0.09, 95% CI [0.03,0.16], p = .006, β = 0.07). Also H5 is mostly supported as people with higher risk perception for the media (b = 0.33, 95% CI [0.25,0.40], p < .001, β = 0.27), economy (b = 0.26, 95% CI [0.18,0.33], p < .001, β = 0.25), and self (b = 0.07, 95% CI [0.02,0.11], p = .004; β = 0.08) have stronger support for regulation. However, for politics, H5 could not be supported (b = -0.00, 95% CI [-0.06,0.06], p = .946).

4.1 Additional exploratory analysis with gender

In contrast to our analysis using weighted data, the model based on unweighted data indicates a second-person effect (see Appendix D.2.1). Therefore, we decided to conduct an additional exploratory analysis with a three-way interaction term involving gender, as the imbalance of gender in the sample appears to influence the outcome of the analysis. The reasoning behind this approach is that gender potentially plays a role with regard to a second-person effect in the context of deepfakes. Indeed, when adding gender as a three-way interaction term (see Appendix D.1.2 for the complete model), we identified a significant difference (b = -0.05, 95% CI [-0.10,-0.00], p = .043, β = 0.09). For male respondents, we find primarily a difference in presumed effects on others but no substantial difference in the presumed effect on self (see Figure 2). In contrast, for females, we observe a potential second-person effect in our data, as the presumed effect on self moderates the relationship of the presumed effect on others. Thus, females with a high presumed effect on others and themselves show the strongest support for regulation. However, the overall pattern remains less clear-cut, as female participants with low values on both variables also indicate relatively high support.

5. Discussion and conclusion

Our study is one of the first to examine the relationship between the perception of deepfake technology and support for its regulation. The results support the existing literature on third-person perception (Corbu et al., 2020; Davison, 1983). When asked about the influence of deepfakes, the perceived effects on one's own opinions are significantly lower than those perceived on the opinions of others. The analysis also sheds light on the behavioral dimension of such third-person perceptions (Gunther & Storey, 2003). The perceived influence of the effects of deepfakes on others is positively related to the support for deepfake regulation. A similar relationship has been found between perceptions of disinformation and regulations of platforms and their content (Chen et al., 2023; Kim, 2025; Riedl et al., 2022). However, our main analysis was unable to identify a second-person effect. Given the small effect size and limited statistical significance in our study, future research should further examine the third-person perception and second-person effects in the context of deepfake regulation.

As we identified differences between the models using weighted and unweighted data, we also focused on gender as part of an exploratory analysis, which was not pre-registered. Our data indicate that a potential second-person effect may apply to female participants but not to male ones. For women, the perceived impact of deepfakes on their own opinions is positively associated with support for deepfake regulation. This might be linked to perceived threats related to deepfake pornography, which predominantly targets women (de Ruiter, 2021; Jungherr & Rauchfleisch, 2025; Rauchfleisch et al., 2025; Wang & Kim, 2022). Although we asked about the effects of deepfakes on opinions, such threats may resonate more strongly with women, leading to a greater inclination to support regulation. This argument is also supported by a significant difference ($t\text{-}Welch(970.57) = 3.28, p = .001$) between males ($M = 3.88$, $SD = 1.88$) and females ($M = 4.22$, $SD = 1.79$) in terms of risk perception for the self. For the other risk perception domains, we do not find such gender differences. For males, the presumed effect of deepfakes on others is positively related to support for regulation, whereas the perceived effect on oneself is not. This noteworthy difference between female and male participants warrants replication and further exploration in future studies, especially given the statistical uncertainty for the estimate of this interaction and the not fully consistent pattern (see Figure 2).

Our study reveals that trust in institutions is positively associated with support for regulating deepfake technology. This finding has practical implications: When trust in institutions is strong, people are more willing to delegate power and responsibility for deepfake regulation. Our measure of institutional trust included politics and journalism as key institutions. In the model following the pre-registration (see Figure 1), we also examined trust in the economy as a predictor, which did not yield any significant association with support for regulation. Further studies could compare the relationship between support for regulation and trust in different kinds of institutions.

The results further confirm that the perceived risks of a technology are positively associated with support for regulation (Gardner & Gould, 1989; Lima et al., 2005). This relationship holds across various application fields. However, contrary to expectations, perceived risks in the political domain do not correlate with support for regulation. This is noteworthy, as previous literature has emphasized the political risks associated with deepfake technology, including its impact on elections and votes (Godulla et al., 2021; Hameleers et al., 2022; Vaccari & Chadwick, 2020). A possible explanation is that the agency for regulation is most likely seen as a political responsibility. As a result, while people may recognize the high risks associated with deepfakes in politics, they may not believe that these risks can be effectively addressed through state-led regulation.

Our study comes with some limitations. First, we use the case of Switzerland, which, due to its direct-democratic instruments (referendums), is a particularly suitable example of a country where public opinion might be relevant when it comes to regulations. However, the generalizability of the findings remains limited, although we cautiously suggest some degree of applicability to other Western European countries. Future studies could compare the link between perceptions of communication technology and support for its regulation in different countries. Furthermore, we also inquired about general aspects of regulation, specifically restrictions on the use of deepfake technology, and did not differentiate between state-led approaches and self-regulation, which studies have shown to be relevant for regulating social media platforms (Chung & Wihbey, 2024; Riedl et al., 2022). Therefore, further studies could investigate different approaches for regulating deepfake technology, considering state-led or self-regulation. Our collected data showed some imbalance regarding gender, which we could address through weighting. While this imbalance affected the result of the assumed second-person effect, other results, such as trust in institutions and risk perceptions, remained stable. Despite the limitations, our study sheds light on the relationship between individual perceptions of deepfake technology and support for its regulation, an issue that is increasingly raised in the public and addressed by politics.

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Appendix

A. Pre-registration

The pre-registration can be accessed on AsPredicted (https://aspredicted.org/s2gt-7rwr.pdf). In the main paper, we discuss in detail only hypotheses H1–H3, H8, and H10. We use a different numbering system in the main paper, labeling them H1–H5. In the appendix, we report the complete analysis with all hypotheses. H11 remained in the pre-registration by oversight, as it was part of an earlier draft and was not carried forward into our final analysis. Here is a list of all pre-registered hypotheses:

H1: Individuals will presume a greater deepfake effect on “others” than on the “self”.

H2: Individuals' presumed deepfake effect on “others” is positively related to their support for the regulation of deepfakes.

H3: Individuals with both high presumed deepfake effects on “others” and “self” will show stronger support for the regulation of deepfakes.

H4: Individuals overestimating deepfakes will show stronger support for the regulation of deepfakes.

H5: Individuals with prior experience with deepfakes will show stronger support for the regulation of deepfakes.

H6: Individuals with prior exposure to deepfakes will show stronger support for the regulation of deepfakes.

H7: Individuals with higher perceived deepfake detection ability will show weaker support for the regulation of deepfakes.

H8: Individuals with higher trust in institutions will show stronger support for the regulation of deepfakes.

H9: Individuals with higher trust in the economy will show lower support for the regulation of deepfakes.

H10: Individuals with higher risk perception of deepfakes for a) politics, b) the media, c) the economy, and d) the “self” will show stronger support for the regulation of deepfakes.

H11: Presumed deepfake effect on others strengthens the positive effect of risk perception of deepfakes on support of regulation of deepfakes.

We also pre-registered an analysis with risk perception of deepfakes as outcome variable. This analysis is completely missing in the main paper due to space constraints. These models are reported in Section D.3. Here are the pre-registered risk perception hypotheses:

H12: Individuals with both high presumed deepfake effects on “others” and “self” will show stronger risk perception of deepfakes.

H13: Individuals overestimating deepfakes will show stronger risk perception of deepfakes.

H14: Individuals with prior experience with deepfakes will show stronger risk perception of deepfakes.

H15: Individuals with prior exposure to deepfakes will show stronger risk perception of deepfakes.

H16: Individuals with higher perceived deepfake detection ability will show weaker risk perception of deepfakes.

H17: Individuals with higher trust in institutions will show weaker risk perception of deepfakes.

B. Measures

B.1. Complete descriptive tables with all variables and items

Table 1. First part of descriptive statistics for all relevant variables and items

Variable	Question/operationalization	M	(*SD*)	n
H1/H3 Presumed effect of deepfakes on self	Deepfakes influence my own opinion.	3.53	(1.70)	1361
H1–H3 Presumed effect of deepfakes on others	Deepfakes influence the opinion of the Swiss population in general.	4.70	(1.45)	1361
(H4) Overestimating deepfakes (3 items, α = 0.73)	(1 = ”do not agree at all”, 7 = ”totally agree”)	4.58	(1.20)	1361
	Deepfakes can be produced for little money.	4.92	(1.47)	1361
	You can create deepfakes yourself with little prior knowledge.	4.36	(1.59)	1361
	Deepfakes are widespread.	4.46	(1.40)	1361
(H5) Prior experience with deepfakes (sum index)	1.11 (0.56)	1361		
	I had already heard about deepfakes before this study	57.02%		776
	I have already seen deepfakes	49.16%		669
	I have already shared or disseminated deepfakes	2.28%		31
	I have already made deepfakes myself	2.65%		36

(H6) Prior exposure to deepfakes (3 items, α = 0.8)	How often do you encounter deepfakes on the following channels? (1 = "Never", 7 = "Often")	3.81	(1.54)	1361
	on social media	4.12	(1.81)	1361
	in messenger apps such as Whatsapp or Telegram	3.31	(1.86)	1361
	on video platforms such as YouTube or Vimeo	4.00	(1.81)	1361
	I am able to distinguish deepfakes from real media content (1 = "do not agree at all", 7 = "totally agree")	3.39	(1.60)	1361
(H7) Perceived deepfake detection ability	(1 = "No trust at all", 7 = "Fully trust")	3.71	(1.31)	1361
H4 (H8) Trust in institutions (2 items, α = 0.74, *Spearman-Brown* = 0.74)	politics	3.62	(1.51)	1361
	media	3.80	(1.43)	1361

Note. Hypothesis numbers in parentheses indicate the pre-registered hypothesis number of a variable.

Table 2. Second part of descriptive statistics for all relevant variables and items

Variable	Question/operationalization	M	(*SD*)	n
(H9) Trust in the economy	(1 = "No trust at all", 7 = "Fully trust")	4.18	(1.37)	1361
H5a (H10a) Risks for politics (2 items, α = 0.89, *Spearman-Brown* = 0.89)	(1 = "do not agree at all", 7 = "totally agree")	4.98	(1.64)	1361
	Deepfakes can be used to manipulate the results of elections in Switzerland.	5.02	(1.71)	1361
	Deepfakes can be used to manipulate the results of referendum votes in Switzerland.	4.95	(1.74)	1361
H5b (H10b) Risks for media (2 items, α = 0.70, *Spearman-Brown* = 0.71)	(1 = "do not agree at all", 7 = "totally agree")	5.81	(1.20)	1361
	Deepfakes can be used to create fake news.	5.48	(1.48)	1361
	Deepfakes can undermine trust in Swiss media.	6.15	(1.24)	1361
H5c (H10c) Risks for economy (2 items, α = 0.81, *Spearman-Brown* = 0.81)	(1 = "do not agree at all", 7 = "totally agree")	4.88	(1.46)	1361
	Deepfake technology developed abroad threatens the Swiss economy.	4.66	(1.61)	1361
	Deepfakes can undermine trust in the Swiss economy.	5.09	(1.57)	1361
H5d (H10d) Risks for the "self" (2 items, α = 0.73, *Spearman-Brown* = 0.73)	(1 = "do not agree at all", 7 = "totally agree")	4.10	(1.83)	1361
	Deepfakes are a problem for my privacy.	4.11	(2.01)	1361
	I'm afraid that someone will create deepfakes with videos of me.	4.08	(2.10)	1361

H2–H5 (H2–H10) Support for deep-fake regulation (4 items, α = 0.77)	(1 = ”do not agree at all”, 7 = “totally agree”)	5.10	(1.45)	1361
	Deepfakes should be banned.	5.28	(1.81)	1361
	I support legislation to ban deepfakes.	5.22	(1.78)	1361
	Deepfakes should be regulated by internet companies like Google and Facebook.	4.85	(2.06)	1361
	Deepfakes should be regulated by the government.	5.04	(1.87)	1361
University degree		27.63%		1361
Gender male		36.00%		1361
Region (French)		33.28%		1361
Age		43.24	(16.28)	1361

Note. Hypothesis numbers in parentheses indicate the pre-registered hypothesis number of a variable.

C. Power analysis

We ran power analyses for the smallest expected effects. For a paired t-test (H1–two-sided) with *Cohen's d* = 0.2, we have a power of 0.9 with n = 265 (calculated with the pwr package in R*)*. We have a power of 0.9 for the regression models with 14 predictors and an effect size of *f2* = 0.02 with n = 1148 (calculated with the pwr package in *R*). For the interaction term (H3), we have a power of 0.93 with a sample size of 1,200, with an effect size of *f2* = 0.01 (power simulation in *R*, $p < 0.05$, *sigma* = 1, *intercept* = 1, *b self* = -0.1, *b others* = 0.1, *b interaction* = -0.1, 1,000 runs).

D. Model results

D.1 Complete models reported in the main paper

This section shows the complete model reported in the main paper. We first compared the gender and age distribution of our sample with the population data of Switzerland at the end of 2023. Although some groups are overrepresented (see the table below), we could generally get observations for each individual group (age and gender). Thus, models with survey weights are used for our analysis. We calculated weights for each single age year between 16 and 79, interlocked with gender (male and female/other).

Table 3. Sample and population data matching the distribution of the Swiss population with our sample

Age group	Gender	Sample count	Population count	Pop. proportion (%)	**Sample proportion (%)**
16–24	Female	157	300,266	5.87%	11.50%
16–24	Male	37	312,723	6.12%	2.72%
25–34	Female	217	382,557	7.48%	15.90%
25–34	Male	72	386,382	7.56%	5.29%
35–44	Female	182	393,599	7.70%	13.40%

35–44	Male	96	385,713	7.54%	7.05%
45–54	Female	124	427,435	8.36%	9.11%
45–54	Male	94	407,681	7.97%	6.91%
55–64	Female	110	503,961	9.86%	8.08%
55–64	Male	87	476,144	9.31%	6.39%
65+	Female	81	606,353	11.90%	5.95%
65+	Male	104	529,525	10.40%	7.64%

D.1.1 Support for regulation weighted data

Table 4. Linear regression model with 95%-CIs shown as LL and UL

Predictors	Estimate	LL	UL	p
Intercept	0.84	0.32	1.35	0.001
H2 Presumed effect on others	0.07	0.01	0.13	0.035
H3 Presumed effect on self X Presumed effect on others	0.02	-0.00	0.05	0.074
H4 Trust in institutions	0.09	0.03	0.16	0.006
H5a Risk politics	-0.00	-0.06	0.06	0.946
H5b Risk media	0.33	0.25	0.40	<0.001
H5c Risk economy	0.26	0.18	0.33	<0.001
H5d Risk for "self"	0.07	0.02	0.11	0.004
Overestimation	0.02	-0.04	0.09	0.497
Experience	-0.09	-0.21	0.03	0.148
Exposure	0.01	-0.04	0.06	0.676
Perceived detection ability	0.05	0.01	0.10	0.027
Trust in the economy	-0.02	-0.08	0.04	0.461
Region (1 = French)	0.38	0.24	0.53	<0.001
Age	0.01	0.00	0.01	0.003
Gender (1 = male)	-0.06	-0.19	0.08	0.414
Education (1 = higher)	-0.06	-0.22	0.09	0.422
Presumed effect on self	-0.04	-0.09	0.01	0.119
Observations R2/R2 adjusted	1361 0.326/0.317			

Note. The outcome variable is support for regulation.

D.1.2 Support for regulation weighted data with gender interaction

Table 5. Linear regression model with 95%-CIs shown as LL and UL

Predictors	Estimate	LL	UL	p
Intercept	0.78	0.26	1.30	0.003
Presumed effect on self X others X Gender	-0.05	-0.10	-0.00	0.043
Presumed effect on self X others	0.05	0.01	0.08	0.008
Presumed effect on self	-0.06	-0.13	0.01	0.078
Presumed effect on others	0.07	-0.01	0.16	0.071
Gender (1 = male)	0.01	-0.14	0.17	0.860
Overestimation	0.03	-0.04	0.09	0.417
Experience	-0.09	-0.21	0.03	0.157
Exposure	0.01	-0.04	0.06	0.737
Perceived detection ability	0.05	0.01	0.10	0.023
Trust in institutions	0.09	0.03	0.16	0.006
Trust in the economy	-0.02	-0.08	0.04	0.477
Risk economy	0.25	0.18	0.33	<0.001
Risk for "self"	0.07	0.02	0.11	0.004
Risk politics	-0.00	-0.06	0.05	0.912
Risk media	0.33	0.25	0.41	<0.001
Region (1 = French)	0.39	0.24	0.53	<0.001
Age	0.01	0.00	0.01	0.003
Education (1 = higher)	-0.06	-0.22	0.09	0.422
Presumed effect on self X Gender (1 = male)	0.05	-0.05	0.15	0.363
Presumed effect on others X Gender (1=male)	-0.01	-0.12	0.10	0.867
Observations R2/R2 adjusted	1361 0.328/0.318			

Note. The outcome variable is support for regulation.

D.2 Model with unweighted data

In this section, we report the model with the unweighted data. The main difference in the model with the weighted data is the observed second-person effect that vanishes when the weighted data are used to represent the age and gender distribution of the Swiss population.

D.2.1 Support for regulation unweighted data

Table 6. Linear regression model with 95%-CIs shown as LL and UL

Predictors	Estimate	LL	UL	p
Intercept	1.06	0.52	1.60	<0.001
Presumed effect on self	-0.06	-0.11	-0.00	0.031
H2 Presumed effect on others	0.07	0.00	0.13	0.038
H3 Presumed effect on self X Presumed effect on others	0.03	0.00	0.05	0.040
Overestimation	-0.02	-0.08	0.05	0.610
Experience	-0.02	-0.14	0.11	0.775
Exposure	0.03	-0.02	0.08	0.275
Perceived detection ability	0.05	0.01	0.10	0.028
H4 Trust in institutions	0.07	0.01	0.14	0.025
Trust in the economy	-0.02	-0.08	0.04	0.493
H5a Risk politics	0.02	-0.04	0.08	0.542
H5b Risk media	0.29	0.21	0.37	<0.001
H5c Risk economy	0.27	0.20	0.35	<0.001
H5d Risk for "self"	0.06	0.01	0.10	0.010
Region (1 = French)	0.30	0.16	0.45	<0.001
Age	0.01	0.00	0.01	0.012
Gender (1 = male)	-0.03	-0.18	0.11	0.648
Education (1=higher)	-0.11	-0.26	0.04	0.161
Observations R2/R2 adjusted	1361 0.297/0.288			

Note. The outcome variable is support for regulation.

D.3 Additional analyses from pre-registration with risk perception as dependent variable

In this section, we report the models with risk perceptions as outcome variables. These analyses were also pre-registered but would go beyond the scope of the current paper. Thus, we report them in the appendix. We also use the weighted data for these models.

D.3.1 Risk for politics

Table 7. Linear regression model with 95%-CIs shown as LL and UL

Predictors	Estimate	LL	UL	p
Intercept	4.70	4.20	5.20	<0.001
Presumed effect on self	-0.02	-0.08	0.05	0.633
Presumed effect on others	0.43	0.36	0.50	<0.001
Overestimation	0.04	-0.03	0.12	0.269
Experience	0.05	-0.10	0.20	0.480
Exposure	0.05	-0.01	0.11	0.111
Perceived detection ability	0.00	-0.05	0.06	0.944
Trust in institutions	0.00	-0.06	0.06	0.979
Region (1 = French)	-0.41	-0.58	-0.24	<0.001
Age	-0.00	-0.01	0.00	0.296
Education (1 = higher)	-0.07	-0.26	0.11	0.439
Gender (1 = male)	0.11	-0.05	0.28	0.178
Presumed effect on self X Presumed effect on others	0.02	-0.01	0.05	0.143
Observations R2/R2 adjusted	1361 0.182/0.175			

Note. The outcome variable is the perceived risk of deepfakes for politics.

D.3.2 Risk for media

Table 8. Linear regression model with 95%-CIs shown as LL and UL

Predictors	Estimate	LL	UL	p
Intercept	4.84	4.47	5.21	<0.001
Presumed effect on self	-0.05	-0.10	-0.01	0.020
Presumed effect on others	0.31	0.25	0.36	<0.001
Overestimation	0.15	0.09	0.21	<0.001
Experience	0.12	0.00	0.23	0.043
Exposure	0.01	-0.04	0.05	0.689
Perceived detection ability	-0.04	-0.08	0.00	0.079
Trust in institutions	0.07	0.02	0.12	0.004
Region (1 = French)	-0.22	-0.35	-0.10	0.001
Age	0.00	-0.00	0.00	0.581
Education (1 = higher)	0.04	-0.10	0.18	0.552
Gender (1 = male)	-0.09	-0.21	0.03	0.154

Presumed effect on self X Presumed effect on others	0.01	-0.01	0.04	0.205
Observations R2/R2 adjusted	1361 0.185/0.178			

Note. The outcome variable is the perceived risk of deepfakes for the media.

D.3.3 Risk for the economy

Table 9. Linear regression model with 95%-CIs shown as LL and UL

Predictors	Estimate	LL	UL	p
Intercept	4.07	3.63	4.51	<0.001
Presumed effect on self	0.05	-0.01	0.10	0.078
Presumed effect on others	0.37	0.30	0.43	<0.001
Overestimation	0.05	-0.02	0.12	0.170
Experience	0.01	-0.13	0.14	0.927
Exposure	0.02	-0.03	0.07	0.486
Perceived detection ability	-0.00	-0.05	0.05	0.895
Trust in institutions	0.05	-0.01	0.11	0.081
Region (1 = French)	-0.05	-0.20	0.10	0.513
Age	0.01	0.00	0.01	<0.001
Education (1 = higher)	-0.17	-0.34	-0.01	0.039
Gender (1 = male)	-0.02	-0.17	0.12	0.758
Presumed effect on self X Presumed effect on others	0.02	-0.01	0.04	0.210
Observations R2/R2 adjusted	1361 0.189/0.181			

Note. **The outcome variable is the perceived risk of deepfakes for the economy.**

D.3.4 Risk for the 'self'

Table 10. Linear regression model with 95%-CIs shown as LL and UL

Predictors	Estimate	LL	UL	p
Intercept	4.35	3.79	4.92	<0.001
Presumed effect on self	0.21	0.14	0.28	<0.001
Presumed effect on others	0.16	0.08	0.24	<0.001
Overestimation	-0.00	-0.09	0.08	0.928
Experience	-0.07	-0.24	0.10	0.430
Exposure	0.08	0.01	0.15	0.023

Perceived detection ability	0.04	-0.02	0.10	0.237
Trust in institutions	0.00	-0.07	0.07	0.957
Region (1 = French)	-0.04	-0.23	0.16	0.703
Age	-0.01	-0.02	-0.00	<0.001
Education (1 = higher)	-0.40	-0.61	-0.19	<0.001
Gender (1 = male)	-0.23	-0.42	-0.04	0.016
Presumed effect on self X Presumed effect on others	0.03	-0.00	0.07	0.079
Observations	1361			
R2/R2 adjusted	0.130/0.122			

Note. The outcome variable is the perceived risk for the 'self'.