# **Title**: **Using Deepfakes to Hack the Human Mind**

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**Abstract:** “Deepfakes” are a new class of AI-generated media. Although these images, videos, and audio may appear genuine, they are actually digital fabrications that give one control over another person’s actions. Concern grows that this new technology may be used to spread disinformation, fuel social tensions, and undermine election outcomes. Yet the psychological impact of Deepfakes has never been systematically studied. Across seven experiments, participants were exposed to genuine or Deepfaked content designed to influence their attitudes and intentions. Results show that even imperfect Deepfakes can manipulate viewers, and bias them just as effectively as authentic content does. Many are unaware of this new technology, find it difficult to detect its presence, and neither awareness nor detection confers protection from its influence.

**One Sentence Summary:** Deepfakes are highly effective in manipulating people’s attitudes and intentions.

**Main Text:** Conventional wisdom tells us that seeing is believing. However, thanks to recent advances in artificial intelligence, this may no longer be the case. A branch of machine learning known as ‘deep learning’ has made it increasingly easy to take a person’s likeness (whether their face, voice, or writing style), feed that data to a computer algorithm, and have it generate a synthetic copy or ‘Deepfake’ (*1*). The results are equal parts impressive and frightening: a digital doppelganger, which can convince others that what they are seeing, reading, or hearing is fact rather than fiction. Although mainly used to mimic real individuals, this technology can also be used to generate images of people who do not exist (*2*), synthetic voices that belong to no one (*3*), and synthetic text that sounds human-authored (*4*).

Deepfaking has quickly become a tool of harassment against activists (*5*), and a growing concern for those in the business, entertainment, and political sectors. The ability to control a person’s voice or appearance opens companies to new levels of identity theft, impersonation, and financial harm (*6-7*). Female celebrities are being Deepfaked into realistic pornographic videos (*8*), and politicians into endorsing controversial positions (*9*). Worry grows that a well-executed video could have public figures ‘confess’ to bribery or sexual assault, political disinformation that distorts democratic discourse and election outcomes (*10*).

Elsewhere, intelligence services and think tanks warn that Deepfakes represent a growing cybersecurity threat, a tool that state-sponsored actors, political groups, and lone individuals could use to trigger social unrest, fuel diplomatic tensions, and undermine public safety (*11-13*). Given the speed with which information proliferates and how quickly individuals, systems, and governments react, these digital lies could be half-way around the world before the truth catches up. And the consequences could be catastrophic.

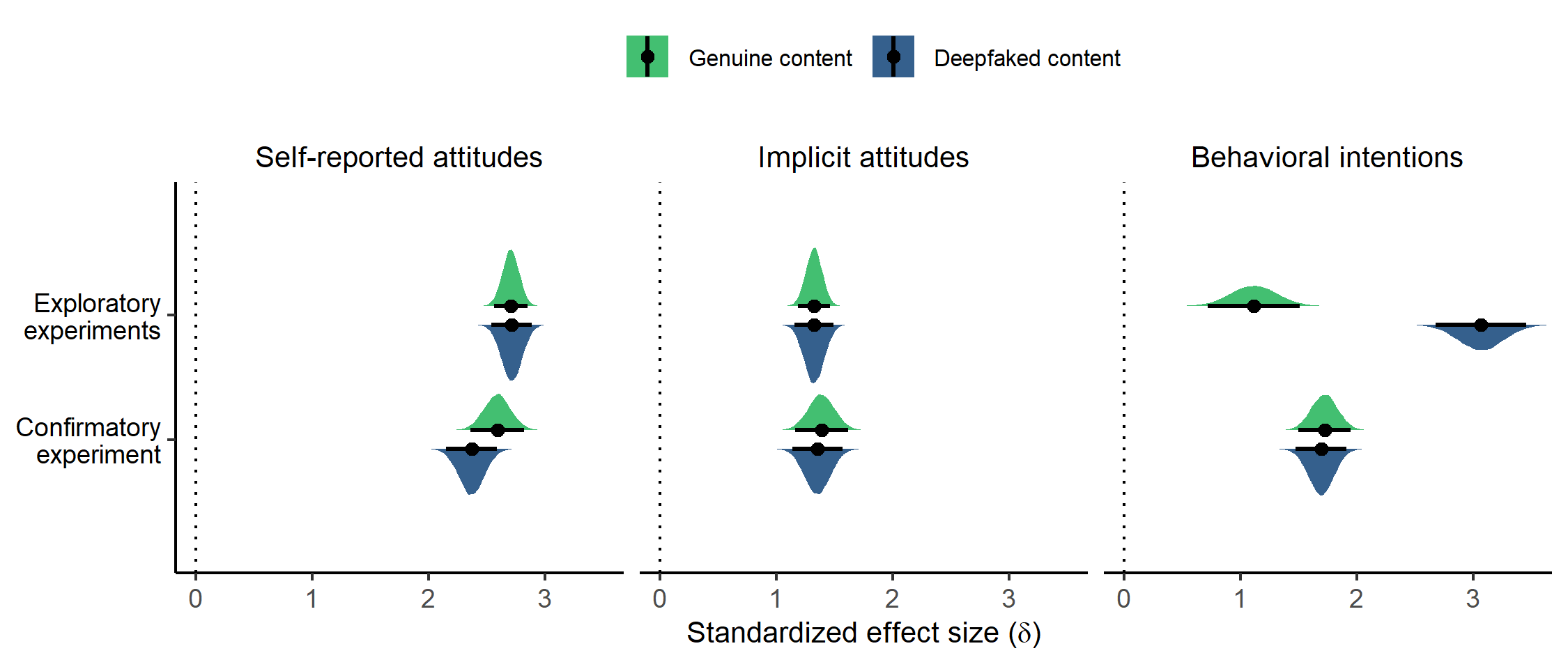
Recognizing these dangers, politicians in Europe and the USA have called for legislation to regulate a technology they believe will further erode the public’s trust in media, and push ideologically opposed groups deeper into their own subjective realities (*14-16*). At the same time, industry leaders such as Facebook, Google, and Microsoft are developing algorithms to detect Deepfakes, excise them from their platforms, and prevent their spread (*17-18*). While these legislative and technological stopgaps are undoubtedly necessary, they are also in a perpetual game of ‘cat-and-mouse’, with certain actors evolving new ways of evading detection and others rapidly working to catch up. In such a world, no law or algorithm can guarantee that the public will be completely protected from Deepfakes.

What is needed then, alongside legislation and technological fixes, is a greater focus on the *human* dimension. It is imperative that we study the impact of this new technology on our thoughts, feelings, and actions. For instance, can Deepfakes be used to manipulate our (implicit) attitudes and intentions? How effective are they in doing so, especially when compared to genuine content? Are people aware of this new technology, and perhaps more importantly, can they detect when they are being exposed to it? Finally, does awareness of Deepfaking and the ability to detect when it is present immunize people from its influence?

We carried out seven pre-registered studies (*n* = 2558) to answer these questions. In Experiments 1-2, we created a set of genuine baseline videos in which an unknown target (‘Chris’) disclosed personal information about himself. In one video, he emitted positive self-statements while in another he emitted negative statements. One group of participants navigated to YouTube (where the videos were hosted), watched the positive or negative variant, and then completed measures of their attitudes and behavioral intentions. We found that genuine online content strongly influenced self-reported attitudes, *δ =* 2.60, 95% CI [2.36, 2.81], *p* < .0001, implicit attitudes, *δ =* 1.37, 95% CI [1.17, 1.62], *p* < .0001, and intentions towards the target, *δ =* 1.74, 95% CI [1.50, 1.95], *p* < .0001 (see Fig 1). [[1]](#footnote-1)

In Experiment 3, a second group encountered a similar procedure but with one key difference: they watched a Deepfaked video. Deepfakes were created by taking the genuine content outlined above, fitting a parameterized 3D model to the target’s head, and using this model to create computer graphical (CG) renderings of his face and mouth movements. These renderings were then converted to photorealistic synthesized video using a trained Generative Adversarial Network (GAN) (*19*), and used to create a set of Deepfakes wherein the target’s actions were manipulated to be either virtuous or selfish. Selectively exposing people to one of these Deepfakes allowed us to control how the target was perceived, liked by some and despised by others (self-reported attitudes: *δ* = 2.24, 95% CI [1.92, 2.53], *p* < .0001; implicit attitudes: *δ =* 1.16, 95% CI [0.85, 1.45], *p* < .0001).

Similar findings emerged when a different Deepfake creation method was used (Experiments 5 & 7), one that generated content from scratch, rather than extracting it from one video and inserting it into another (*20*). Here we took pre-existing footage from a different actor and used it to generate a 3D head model. This model was then used to perform iterative localized edits on the genuine videos (i.e., to transform positive statements into negative statements and vice-versa). Digitally manipulating the target’s actions in this way allowed us to once again control attitudes and intentions towards him (self-reported attitudes: *δ =* 2.35, 95% CI [2.15, 2.59], *p* < .0001; implicit attitudes: *δ =* 1.36, 95% CI [1.14, 1.57], *p* < .0001; behavioral intentions: *δ =* 1.70, 95% CI [1.48, 1.91], *p* < .0001) (see Fig 1).



**Fig 1**. Standardized effect sizes, 95% confidence intervals, and distributions for self-reported attitudes, implicit attitudes, and behavioral intentions for those exposed to genuine and Deepfaked online content. ‘Exploratory experiments’ refers to combined effects from Experiments 1-6 while ‘Confirmatory experiment’ refers to effects from the pre-registered, high-powered confirmatory study (Experiment 7).

The above findings also generalized from one synthetic media type (video) to another (audio). In Experiments 4 & 6, we created a training set of the target’s voice and then fed it to a bidirectional text-to-speech (TTS) autoregressive neural network (*21*). This resulted in a Deepfake of the target’s voice: a synthetic replica that sounded like the original, and which could be manipulated into saying anything. Participants were informed that they would listen to a recording of Chris, and were exposed to the Deepfaked voice, or a genuine recording of him emitting positive or negative self-statements. By synthetically cloning a person’s voice and manipulating what he ‘said’, we were able to control the viewer’s attitudes and intentions in ways that were similar to Deepfaked videos (self-reported attitudes: *δ =* 3.21, 95% CI [2.97, 3.47], *p* < .0001; implicit attitudes: *δ =* 1.41, 95% CI [1.17, 1.65], *p* < .0001; behavioral intentions: *δ =* 3.06, 95% CI [2.68, 3.46], *p* < .0001) (see Fig 1).

Taken together, our findings show that Deepfakes can be used to bias what people think and feel. Yet how *effective* they are in doing so? Most - including our own - contain video or audio artefacts, which represent ‘tell-tale’ signs of manipulation. It is possible that these artefacts undermine the effectiveness of Deepfakes relative to genuine content. Yet, in our studies, this was not the case: Deepfakes were statistically non-inferior to genuine content (i.e., 91% as effective in altering self-reported attitudes (95% CI [80.2, 103.3]), 97% as effective in altering implicit attitudes (95% CI [76.1, 121.1]), and 98% as effective in altering intentions compared to genuine content (95% CI [81.4, 117.7]).

It is also worth asking if (a) people are aware that online content can be Deepfaked, and (b) if they can detect when they are exposed to it. Our findings were not encouraging: a large number of participants had never heard of Deepfaking prior to the study (44%), and even after they were told what it entailed, many were unable to determine if the content they had encountered was genuine or Deepfaked in nature. That is, they did not make accurate (Balanced Accuracy = .68, 95% CI [.63, 0.73]) nor informed (Youden’s *J* = .36, 95% CI [.26, .45]) judgements about the authenticity of what they were seeing or hearing. Nevertheless, people who were aware of Deepfaking were nearly twice as likely to detect when they were exposed to it relative to their unaware counterparts (Incidence Rate Ratio = 1.87, 95% CI [1.44, 2.53]).

Finally, does an awareness of Deepfaking, or an ability to detect when it is present, protect the viewer from its influence? Unfortunately, this was never the case in our studies. Aware individuals were manipulated by Deepfakes just as their unaware counterparts were (self-reported attitudes: *δ =* 2.10, 95% CI [1.83, 2.41], *p* < .0001; implicit attitudes: *δ =* 1.29, 95% CI [1.03, 1.59], *p* < .0001; behavioral intentions: 1.51, 95% CI [1.21, 1.80], *p* < .0001). Those who correctly detected that they were exposed to a Deepfake also fell prey to its influence (self-reported attitudes: *δ =* 2.18, 95% CI [1.93, 2.44], *p* < .0001; implicit attitudes: *δ =* 1.37, 95% CI [1.12, 1.64], *p* < .0001; behavioral intentions: 1.59, 95% CI [1.34, 1.84], *p* < .0001). Deepfake even changed the attitudes of those who were aware *and* detected its presence (self-reported attitudes: *δ =* 1.98, 95% CI [1.65, 2.27], *p* < .0001; implicit attitudes: *δ =* 1.35, 95% CI [1.01, 1.65], *p* < .0001) and intentions (*δ =* 1.38, 95% CI [1.09, 1.72], *p* < .0001).

In short, even detectable or imperfect Deepfakes psychologically impact viewers, and can be used to manipulate their attitudes and intentions as effectively as genuine content. Many are unaware of this new technology, find it difficult to detect when they are being exposed to it, and neither awareness nor detection serves to protect them from its influence.

Given the dangers posed by Deepfaking, politicians are looking to the law to help regulate its creation and spread, while industry leaders devise algorithms to help detect and recognize when it’s present. Yet our findings indicate that this won’t be enough: a single brief exposure to a Deepfake quickly and effectively shifted (implicit) thoughts and feelings, even when people were fully aware that the content they had just encountered was Deepfaked.

What is needed then is a better understanding of the *Psychology* *of Deepfakes*, and in particular, how they exploit our cognitive biases, vulnerabilities, and limitations for maladaptive ends. We need to identify the properties of individuals, situations, and content that increase the chances that Deepfakes are believed and spread. Examine if these lies root themselves quickly and deeply in our minds, and linger long after efforts to debunk them have ended (*22*). If so, then corrective approaches currently favored by tech companies, such as tagging Deepfaked content with a warning, may be less effective than assumed (*23*). We also need to examine if Deepfakes can be used to manipulate what we remember, either by trigger Mandela effects (i.e., installing false memories of events that never happened) or by altering genuine memories that did (*24*). If they can influence memory then it is not only the present and future that can be influenced but also the past.

Perhaps the most dangerous aspect of Deepfakes is their capacity to erode our underlying belief in what is real and what can be trusted. Instead of asking if a specific image, video, or audio clip is authentic, this new technology may cause us to question *everything* that we see and hear, thereby accelerating a growing trend towards epistemic breakdown: an inability or reduced motivation to distinguish fact from fiction. This “reality apathy” (*25*) may be exploited by certain actors to dismiss inconvenient or incriminating content as a fabrication (the so-called ‘liar’s dividend’ (*26*)). Given that the human mind is built for belief (*27*), we need psychological interventions that can inoculate individuals against Deepfakes, and together with technology and legislation, create a shared immune system that safeguards our individual and collective belief in truth (*28*). Without such safeguards we may be speeding towards a world where our ability to agree on what is true eventually disappears.

**References and Notes**

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1. A similar set of outcomes emerged across our various studies. We opted to report the analyses from our final confirmatory study, unless otherwise noted, as it represents the strongest (pre-registered) test of our hypotheses. For a detailed breakdown of each individual study, see Supplementary Materials. [↑](#footnote-ref-1)