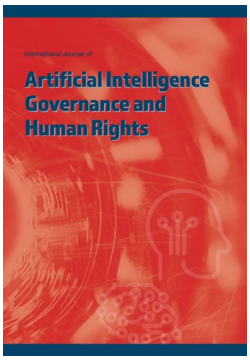

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Navigating ethical dilemmas: the role of deepfake technology in modern advertising campaigns

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Navigating ethical dilemmas: the role of deepfake technology in modern advertising campaigns

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Abstract: This study investigates the ethical implications and audience perceptions of deepfake technology – AI-generated synthetic media – in modern advertising. Deepfakes enable realistic manipulation of visual and audio elements, opening creative possibilities but also raising serious concerns about authenticity, consent, and misinformation. Using a primarily quantitative mixed-method design, data were collected from 153 respondents across different age groups and technological backgrounds. The Affinity for Technology Interaction (ATI) scale, demographic profiling, and visual assessments were used to examine awareness and acceptance of deepfake advertising. Statistical tests revealed significant differences in perception by gender and age: younger, tech-savvy participants showed greater tolerance for deepfake content but still expressed ethical unease. Respondents preferred the term *artificial media* over *deepfake* for its neutral connotation. The results highlight the urgent need for ethical guidelines and disclosure norms to ensure responsible adoption of AI-generated media in marketing while safeguarding consumer trust.

Keywords: advertising campaigns; ATI; attitude toward internet; DL; deep learning; deepfake technology; ethical implications.

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1 Introduction

The advent of deepfake (Westerlund, 2019) has made it feasible to create incredibly lifelike videos depicting individuals engaging in activities that have never really taken place. Deepfake is a relatively new phenomenon that has the potential to significantly affect society. By combining the reach and accessibility of social media with persuasive deepfake content, massive audiences may be reached in a flash. As a result, deepfake has become notorious and terrifying due to the proliferation of these fake films, which causes fear in many people. It is now physically difficult to tell real videos from false ones due to the development of deepfake technologies. Applications based on Artificial Intelligence (AI) such as FaceSwap (Kowalski, 2021) and Face2Face (Thies et al., 2016) have seen extensive use for facial expression swapping in photos and videos. It is feasible to alter a person's look, hairdo, age, lip movement, and other physical attributes with such face-adjusting techniques. A large part of the growth of deepfake methods can be attributed to the developments in computer vision and DL technology. The term 'deepfakes' describes the use of Deep Learning (DL) technology to train deep neural networks (DNNs) to generate false material. Artificial DNNs that mimic the structure and communication processes of biological brains can be programmed to synthesise hyper-realistic but false alternative content by automatically combining, replacing, and superimposing images, videos, and other media over a predetermined video (Kietzmann et al., 2020; Maras and Alexandrou, 2019). The artistic talent of a human is not necessary for the automatic creation of deepfakes. The ability to generate and manipulate information by learning for massive datasets makes deepfake creators change the movements, facial expressions, and even entire identities (Singh et al., 2022). Deepfakes are a new kind of fake content creation that differs greatly from popular

current methods of editing, such as Photoshop or CGI. To achieve this, deepfakes rely on a particular network architecture known as an 'autoencoder'. This architecture is responsible for comprehending, encoding, and compressing important features of the source image, such as an individual's skin tone, head direction, and the movement of their lips and eyes. Then, the compressed version can be decoded to generate a fake face. A large amount of training data (such as face movies) is needed for the encoder to 'learn' the key characteristics of its topic. When the auto-encoder has learnt the ins and outs of the face's 'workings,' the decoder will have all the knowledge it needs to make the face in the video say or do anything. It does not matter if the image of the person it was trained on already existed or not; it may generate any image. Worries in several areas have been heightened by the proliferation of profound fake movies and photos. It is possible to influence public opinion and undermine public faith in political campaigns with deepfakes (Vaccari and Chadwick, 2020). With this technology, it's possible to stage phoney meetings and speeches that misrepresent officials, leading to the spread of misinformation. In the entertainment sector, deepfakes can be used to steal celebrities' identities and damage their reputations by superimposing their photos onto express happy. Deep fakes can also undermine the credibility of media outlets and make it harder to check the integrity of news stories by erasing the distinction between fact and fiction. In addition to the aforementioned domains, deep fake technology poses risks to trust, security, and privacy in a wide range of social settings.

Because of their capacity to create dynamic, engaging, and personalised content, deepfakes have the opportunity to completely transform the advertising industry. Nevertheless, there are concerns about consumer deceit, privacy invasion, lack of permission, and the decline of faith in the media that come along with this possibility. This study aims to promote transparency, respect for individual rights, and alignment with society values in the use of deepfake technology by investigating these concerns and identifying the ethical boundaries and obligations that advertisers must manage. From the vantage points of advertising ethics, consumer protection, legal norms, and technological accountability, this project will examine the ramifications of deepfake technology using a multidisciplinary approach. With any luck, this study's findings will help shape industry standards, direct policymaking, and lay the groundwork for an ethical framework for deepfakes in advertising, all of which will lead to a more reliable and moral online media landscape.

2 Literature reviews

Research on **deepfake technology** – AI-driven systems that generate synthetic visual and audio content – has grown rapidly, but its ethical and advertising implications remain under-examined. Earlier work by Agarwal and Nath (2023) revealed that consumers often find deepfake advertisements deceptive yet simultaneously engaging when the content is personalised and relatable. Building on this, Campbell et al. (2022) demonstrated that the realism achieved through advanced manipulation heightens both imaginative appeal and the risk of perceived deceit. Comparing these findings suggests a persistent tension between creativity and credibility: the same technological sophistication that attracts attention may erode trust.

Empirical research by Sivathanu and Pillai (2023) on deepfake hotel videos identified *media richness* and *perceived value* as key factors influencing booking intentions. Their

model indicates that visual immersion can outweigh scepticism when consumers perceive informational benefits. In contrast, Powers et al. (2023) found that disclosing the synthetic nature of an ad lowers purchase intention by reducing perceived source trustworthiness. Taken together, these results imply that *transparency strategies* must balance honesty with persuasive impact.

From a cognitive-psychological perspective, Whittaker (2024) reported that viewers' processing of deepfake imagery depends on the realism level and presentation context – too authentic and audiences feel manipulated, too artificial and engagement declines. Sivathanu et al. (2023) extended this by showing that personalisation and information-manipulation tactics jointly influence online shopping behaviour. The emerging consensus across these studies is that consumers' ethical judgements hinge on *contextual framing* and *trust cues* rather than on deepfake technology itself.

Beyond marketing, scholars have examined the **legal and ethical dimensions** of generative AI. Hirsch (2023) linked deepfakes to corporate-risk governance, arguing that responsible innovation requires integrating AI oversight into strategic management. Langer and Wyczik (2020) highlighted gaps in existing law, while Meskys et al. (2020) advocated a 'nuanced regulation' that fosters creativity without enabling harm. Conversely, Kasita (2022) and Ransom (2023) warned of gender-based exploitation and privacy violations, calling for urgent legal safeguards. Comparative analyses by Tuysuz and Kılıç (2023) and Ruiter (2021) reinforce the need for a global ethical framework that reconciles innovation with human-rights protection.

Overall, previous literature establishes three patterns:

1 **Technological duality** – deepfakes simultaneously enhance engagement and threaten authenticity.

2 **Perceptual variability** – demographic and cognitive traits mediate trust responses.

3 **Regulatory insufficiency** – current laws and ethical codes lag behind practice.

Yet, empirical studies that integrate these perspectives within advertising contexts remain scarce. Most existing work isolates either technical or legal aspects and overlooks **consumer perception** as the central determinant of ethical acceptance. Addressing this gap, the present study investigates how individuals of differing age and gender evaluate deepfake advertising through the lens of the **Affinity for Technology Interaction (ATI) Scale**, thereby linking marketing ethics, technology acceptance, and regulatory insight within a unified empirical framework.

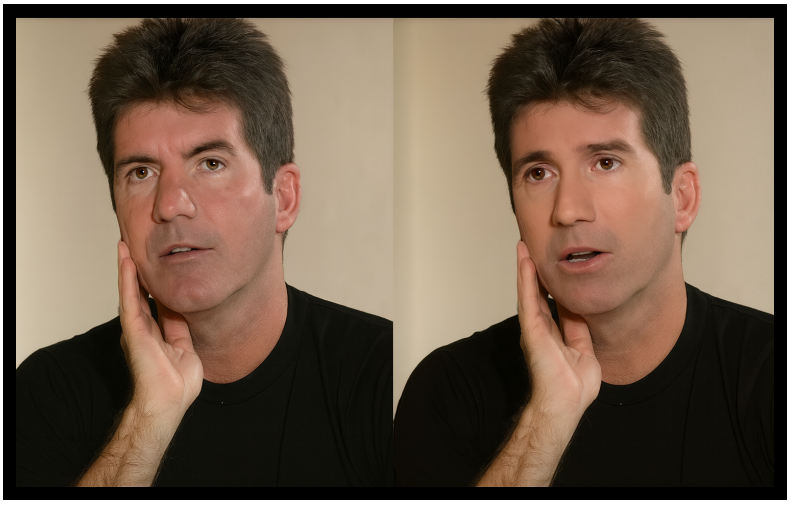
3 Experimental methods and materials

The amount of deepfake ads has been on the rise since the pandemic began. Nevertheless, research on the moral consequences of deepfake technology's use in ads is lacking. Because of this, this research is necessary. The ethical consequences of using deepfake technology in advertising campaigns were examined in this study using a qualitative research approach. The goal of going with a qualitative approach was to get a good feel for the range of opinions held by both customers and specialists in the field of this technology. Technological advancements in the field of deepfake picture creation open up new avenues of inquiry into representation, creativity, art, and pure imagination.

By using these photos, well-known people can be brought back for economic purposes, as well as for historical or artistic ones, guaranteeing that they will be remembered for years to come.

Figure 1 illustrates the visual stimuli used in the study for pre- and post-assessment of respondents' perceptions.

Figure 1 Image used in the study for pre and post assessment (see online version for colours)



3.1 Research design

This study adopts a **quantitative, cross-sectional design** supplemented by limited qualitative feedback to capture respondents' attitudes toward deepfake advertising. The approach combines **descriptive**, **exploratory**, and **empirical** elements. The descriptive component identifies participant characteristics, while the empirical aspect tests hypotheses related to demographic differences in perception. A semi-structured online questionnaire was used as the principal instrument for primary data collection.

The study focused on understanding how audiences interpret, trust, and ethically evaluate advertisements created through **deepfake technology**, also referred to as *artificial or synthetic media*. Two visual stimuli (pre- and post-exposure images) were shown to participants to assess changes in perceived authenticity and comfort levels.

3.2 Sampling and participants

A **simple random sampling** technique was employed to ensure diversity across age, gender, and professional background. Participants were voluntarily recruited online through social media and academic networks. Prior to participation, they were informed of the study's academic purpose, assured of confidentiality, and provided consent for data use.

Out of 200 distributed questionnaires, **153 valid responses** were retained after data cleaning. Respondents represented multiple occupational categories, including students, professionals, and entrepreneurs. Each online interaction lasted approximately 25–30 min and was conducted between **January and May 2024**.

3.3 Instrumentation and variables

The questionnaire consisted of three key parts:

1 **Demographic Profile** – capturing age, gender, education, and employment status.

2 **Technology Affinity Assessment** – using the **Affinity for Technology Interaction (ATI) Scale** developed by *Franke et al.* (*2019*), which measures an individual's comfort and enthusiasm in using digital technologies ($\alpha = 0.832$).

3 **Perception of Deepfake Advertisements** – evaluating authenticity, comfort, realism of lip and facial movements, and terminology preference (e.g., *deepfake*, *artificial media*).

All items were measured on a **six-point Likert scale** ranging from 1 ('Not true at all') to 6 ('Completely true').

3.4 Data collection and coding process

Data were gathered via **Google Forms**, exported into **SPSS Version 23**, and analysed following a structured process:

1 **Data cleaning:** Removal of incomplete responses and verification of consistent scaling.

2 **Coding:** Assigning numeric codes to categorical variables (gender, age group, terminology preference).

3 **Reliability testing:** Computing **Cronbach's alpha** to ensure internal consistency of the ATI construct.

4 **Statistical analysis:** Applying univariate (frequency, mean, SD), bivariate (independent-sample *t*-test, Chi-square test), and multivariate (Cramer's V correlation) analyses.

5 **Interpretation:** Comparing group differences and examining associations between technological affinity, demographic variables, and ethical perception of deepfakes.

3.5 Ethical considerations

The research adhered to ethical standards of academic inquiry. Respondents participated voluntarily, with anonymity and data confidentiality guaranteed. The visual material used for testing was ethically sourced and non-identifiable. The study aimed to promote awareness of digital ethics rather than endorse or reproduce deceptive practices.

3.6 Hypotheses

Based on the literature and objectives, the following hypotheses were formulated:

- H_{01}: There is no significant difference in Affinity for Technology Interaction (ATI) across genders.
- H_{02}**:** There is no significant difference in ATI scores across age groups.

- H_{03}: Participants with higher ATI scores perceive deepfake advertisements as equally non-authentic before and after exposure.

4 Results and discussions

4.1 Demographic overview

Out of 153 valid respondents, 54.9% were male and 45.1% female, representing a balanced gender distribution. Most participants (41.2%) were aged **18–24**, followed by 45–54 (21.6%), indicating a strong youth representation with meaningful mid-career engagement. Over **64% used the internet for 1–5 h daily**, reflecting moderate digital exposure typical of technologically literate consumers. Nearly half were students, showing the growing influence of younger, digitally active audiences in shaping advertising perceptions.

This demographic spread ensures that responses reflect both digitally native and mature user perspectives, making the findings representative of the broader consumer base exposed to deepfake advertising.

4.2 Reliability and validity

The **Affinity for Technology Interaction (ATI) scale** achieved a **Cronbach's alpha of 0.832**, confirming strong internal consistency (Table 4). This reliability aligns with benchmarks from Franke et al. (2019), establishing that participants' self-reported technological affinity can be trusted as a valid measure of their interaction comfort with AI-generated content.

4.3 Gender differences in technology affinity (H_{01})

Results of the independent-sample *t*-test show a statistically significant difference in ATI mean scores between genders ($t = -2.114$, $p = 0.036$). Male participants reported slightly higher technological affinity (M = 3.93) than females (M = 4.25). This suggests that men display greater confidence in using and understanding technology-based media, consistent with earlier meta-analyses by Whitley (1997) and Cai et al. (2017).

However, the gap is narrowing; female participants exhibited growing awareness and scepticism, indicating a maturing perception rather than disengagement. This points to a nuanced understanding where both genders recognise deepfake potential but vary in tolerance toward its ethical implications.

4.4 Age variations in perception (H_{02})

The Chi-square test revealed a **significant relationship** between age group and ATI range ($\chi^2 = 15.14$, $p = 0.019$). Younger respondents (18–24) largely fell in the *medium* ATI range, while the 25–34 group showed higher technological engagement. This confirms that digital natives adapt faster to AI-driven media but are also more aware of manipulation risks.

The Chi-square test results examining the relationship between age group and ATI range are presented in Table 6.

These findings echo Iacobucci et al. (2021), who argued that deepfake detection awareness curbs content sharing behaviour among younger users. Thus, awareness acts as both a protective and limiting factor – reducing blind trust but also moderating enthusiasm for immersive marketing.

4.5 Authenticity perception and ethical awareness (H_{03})

The **Cramer's V (0.253, $p = 0.003$)** indicates a moderate, statistically significant relationship between perceived authenticity and affinity for technology. Participants comfortable with technology did not necessarily view deepfakes as more authentic, but rather showed better analytical discrimination between genuine and synthetic visuals.

Table 7 results show that 63.2% of respondents partly agreed that the image 'seems authentic,' yet 42.9% found lip movements unrealistic. This mixed perception highlights a cognitive split – respondents enjoy deepfake realism but simultaneously question its truth value. Such findings support Greengard (2019), who described this paradox as the 'trust–deception dilemma' of synthetic media.

The strength of association between the variables is further confirmed by the symmetric measures reported in Table 8.

4.6 Terminology preference and framing effects

When asked which term carries the least negative association, '**Artificial Media'** ranked highest (39.2%), followed by *Deepfake* (30.1%). When asked which best describes the technology, nearly **47%** again chose *Artificial Media*. This indicates that language framing significantly influences ethical acceptance – a finding aligned with Rodríguez Abellán (2021), who noted that culturally neutral terminology reduces resistance to new media technologies.

For advertisers, this means that transparent yet neutral descriptors can foster trust without downplaying the use of synthetic technology.

4.7 Interpretive discussion

The results collectively suggest that **technological familiarity increases tolerance** for deepfake use in advertising but does not eliminate ethical concern. Participants with higher ATI scores can differentiate synthetic from authentic content yet remain cautious of misinformation risks.

These findings align with Campbell et al. (2022), who emphasised that the success of AI-based advertising depends on the balance between innovation and disclosure. Similarly, Powers et al. (2023) found that full transparency reduces purchase intent but enhances brand credibility – an effect also visible in this study's respondent behaviour.

From a managerial perspective, brands must **communicate authenticity proactively** – through disclaimers, ethical AI statements, or verified content markers – to preserve consumer confidence. At the policy level, **advertising councils and digital regulators** should develop certification mechanisms that distinguish creative deepfake use from manipulative deception.

4.8 Synthesis of findings

Hypothesis	*Result*	*Interpretation*
H_{01} (Gender Difference)	Rejected ($p = 0.036$)	Gender influences perception; males more tech-comfortable, females more cautious
H_{02} (Age Difference)	Rejected ($p = 0.019$)	Younger respondents more adaptive yet sceptical
H_{03} (Authenticity View)	Rejected ($p = 0.003$)	High-tech-affinity groups discern synthetic media without blind trust

Overall, the study demonstrates that **demographics and digital literacy jointly shape ethical evaluations** of AI-generated advertising. Deepfake technology may revolutionise marketing creativity, but its adoption must be guided by principles of consent, disclosure, and responsibility.

Table 1 Demographic profile

	Frequency	*Percentage* (%)
Gender of the respondents		
Male	84	54.9
Female	69	45.1
Age group of the respondents		
18–24 years	63	41.2
25–34 years	32	20.9
35–44 years	25	16.3
45–54 years	33	21.6
Work status		
Student	65	42.5
Employed	45	29.4
Unemployed	32	20.9
Business	11	7.2
Marital status		
Single	101	66.0
Married	52	34.0
Frequency of internet usage (per day in past 6 months)		
1 h or less	26	17.0
1–5 h	99	64.7
5–10 h	18	11.8
10 h and above	10	6.5

Table 1 Demographic profile (continued)

	Frequency	*Percentage* (%)
Working experience		
1 year or less	74	48.4
1–3 years	26	17.0
3–5 years	20	13.1
5–10 years	19	12.4
More than 10 years	14	9.2
Income per month		
Less than Rs. 40,000	41	26.8
Rs. 40,001–Rs. 80,000	38	24.8
Rs. 80,001–Rs. 1,20,000	32	20.9
Rs. 1,20,001–Rs. 1,50,000	16	10.5
More than Rs. 1,50,000	26	17.0

The data collected from 153 respondents reveals interesting insights with largest group among them comprising of students, with a total of 65 individuals, accounting for 42.5% of the total respondents. The next significant category is employed respondents, consisting of 45 individuals or 29.4%. Unemployed respondents make up 20.9% of the sample, with a total of 32 individuals. Lastly, individuals involved in business account for 7.2% of the respondents, with 11 individuals. These statistics clearly indicate that students form most of the respondents, followed by the employed individuals, while a smaller proportion represents the unemployed or those engaged in their own businesses. Displaying the distribution of survey respondents' marital status, 34.0% of the people are married, while 66.0% of its members are single. 64.7% of respondents said they used the internet for 1–5 h per day. One hour or fewer of internet use per day was reported by a smaller proportion (17.0%). likewise, 11.8% of respondents said they used the internet for 5–10 h every day, while 6.5% of respondents said they used it for 10 h or longer.

When looking at the respondents' working experience, the largest group is 48.4%, who have had one year or less of employment. With 17.0% of the total, people with one to three years of experience make up the next largest group. Following this are 13.1% of responders who have between three and five years of experience. Ninety-two percent of the population has more than 10 years of experience, while 12.4% of respondents had 5–10 years. The categorisation of respondents' monthly income reveals that 26.8% earn less than Rs. 40,000, 24.8% earn between Rs. 40,001 and Rs. 80,000, 20.9% earn between Rs. 80,001 and Rs. 1,20,000, 10.5% earn between Rs. 1,20,001 and Rs. 1,50,000, and 17.0% earn more than Rs. 1,50,000 per month.

Table 2 shows the distribution of respondents by gender across three ATI (Attitude Towards Internet) range categories: low, medium, and high. The dataset analysed in this study consisted of 11 respondents falling within the low ATI range (1.00–2.669). Among these participants, 63.6% were male, while 36.4% were female. Moving on to the medium ATI range (2.67–4.339), a larger sample of 82 respondents was included, with males accounting for 52.4% and females comprising 47.6% of the group. Lastly, within the high ATI range (4.34–6.00), there were 60 respondents, with males representing 56.7% and females constituting 43.3% of the sample.

Table 2 Gender and the ATI scale

			Gender of the respondents		
			Male	*Female*	*Total*
ATI range	1.00–2.669 (low)	Count	7	4	11
		% within ATI Range	63.6%	36.4%	100.0%
	2.67–4.339 (medium)	Count	43	39	82
		% within ATI Range	52.4%	47.6%	100.0%
	4.34–6.00 (high)	Count	34	26	60
		% within ATI Range	56.7%	43.3%	100.0%
Total		Count	84	69	153
		% within ATI Range	54.9%	45.1%	100.0%

Table 3 presents the distribution of respondents' education levels across three ATI range categories: low, medium, and high. There are eleven responders in the low ATI range (1.00–2.669). Of them, 9.1% hold a master's degree or above, and 90.9% have a bachelor's degree. There are no responders who have only completed their elementary schooling, high school education, or doctorate. 82 responders fall into the medium ATI range (2.67–4.339). 87.8% of the population holds a bachelor's degree. Furthermore, 2.4% hold a PhD, 2.4% have completed elementary school, 1.2% have a diploma, and 6.1% have a Master's degree or above. Within the 4.34–6.00 high ATI range, 60 responders are found. In this instance, 80.0% of the population holds a bachelor's degree, 8.3% holds a master's degree or above, 5.0% has just completed elementary school, 5.0% holds a PhD, and 1.7% holds a diploma.

Table 3 Education and ATI range

			Education level of respondents					
			Primary school	*Diploma*	*Bachelor degree*	*Masters or higher*	*Doctorate*	*Total*
ATI Range	1.00–2.669 (low)	Count	0	0	10	1	0	11
		% within ATI Range	0.0%	0.0%	90.9%	9.1%	0.0%	100.0%
	2.67–4.339 (medium)	Count	2	1	72	5	2	82
		% within ATI Range	2.4%	1.2%	87.8%	6.1%	2.4%	100.0%
	4.34–6.00 (high)	Count	3	1	48	5	3	60
		% within ATI Range	5.0%	1.7%	80.0%	8.3%	5.0%	100.0%
Total		Count	5	2	130	11	5	153
		% within ATI Range	3.3%	1.3%	85.0%	7.2%	3.3%	100.0%

Adequate internal consistency of the ATI scale was ensured through the calculation of Cronbach's alpha as indicated in Table 4. The Cronbach's alpha value of 0.832 reflects a high level of reliability. Previous research studies suggest that values falling between 0.83 and 0.94 can be considered as benchmarks for internal consistency, a consensus drawn from various sources. In terms of the sample participants, the average ATI score was found to be 4.07 with a standard deviation of 0.96.

H_{01}: The participants' self-assessment of their affinity for technology results in a high degree of dissociation between genders.

Table 4 Measurement of internal consistency

Construct	*Number of items* (*number inverted*)	*Scale mean/SD*	*Cronbach's alpha*	*Reference Cronbach's alpha* (*Franke et al., 2019, p.9*)
ATI scale	9 (3)	4.07 /0.96	0.832	0.83–0.94 (Mean Range: 3.58–4.41)

The data presented in Table 5 illustrates the outcomes of an independent sample t-test that examines the average ATI scores among male and female participants. The t-test demonstrates a statistically significant distinction in the mean ATI scores between male and female respondents, with a t value of –2.114 and a p-value of 0.036. As the p-value is below the predetermined threshold of 0.05, we can reject the null hypothesis, which suggests that there is no disparity in ATI scores based on gender. Consequently, it can be inferred that gender has a significant impact on ATI scores, with males displaying a higher average ATI score in comparison to females. Moreover, gender disparities in attitudes toward technology have been shown by meta-reviews (Cai et al., 2017; Whitley, 1997), with males generally tending to have slightly more positive sentiments.

H_{02}: There are no significant differences in the participants' self-assessed affinity for technology values depending on the age.

Table 5 Independent sample t-test

Gender of the respondents		*N*	*Mean*	*Std. deviation*	*Std. error mean*	*t value*	*df*	*p-value*
Mean ATI	Male	84	3.927	1.004	0.110	–2.114	151.000	0.036
	Female	69	4.254	0.885	0.107			

The statistical analysis using the Pearson Chi-square test revealed a significant relationship between age group and ATI range, as evidenced by a chi-square value of 15.14 and a p-value of 0.019. Given that the p-value is below the threshold of 0.05, we can confidently reject the null hypothesis that there is no association between age group and ATI range. This implies that individuals' attitudes towards the internet differ significantly based on their age groups. Notably, the 18–24 age group exhibited the highest number of respondents falling within the medium ATI range, while the 25–34 age group showed a relatively higher percentage of respondents in the high ATI range. Deepfake detection thereafter has a detrimental effect on users' sharing intentions,

constraining the theoretical harm of deepfake at the very foundation of one of its advantages, according to a serial arbitration analysis of various age groups (Iacobucci et al., 2021).

H_{03}: The participants of the group with a high affinity for technology consider the deepfake advertisement after the treatment as non-authentic as before the treatment.

The degree of agreement that respondents had with different assertions about the comfort, authenticity, realism of lip motions, and realism of facial expressions in an image is displayed in Table 7. 'The image seems authentic' is something that many respondents (63.2%) somewhat agree with (Partly True). Responses to the image's comfort level were mixed; most respondents (37.5%) said it was 'Partly True'. More people expressed scepticism in their responses when asked if lip motions were realistic; a sizable portion (42.9%) said this was 'Not quite true'. There was a wide range of opinions on the realism of facial expressions; the categories with the highest replies were 'Partly True' (40%) and 'Not quite true' (32.5%).

Table 6 Chi-square test

		ATI Range				*Pearson Chi-square*	*df*	*p-value*
		1.00–2.669 (low)	*2.67–4.339 (medium)*	*4.34–6.00 (high)*	*Total*			
Age group	18–24 years	4	38	21	63	15.14	6	0.019
	25–34 years	5	9	18	32			
	35–44 years	1	12	12	25			
	45–54 years	1	23	9	33			
Total		11	82	60	153			

Table 7 Cramer V test

		Please indicate again your level of agreement with the following statements.				
		The image seems authentic	*I felt comfortable with the image*	*The lip movements are realistic*	*The facial expressions are realistic*	*Total*
The image looks authentic	Not true at all	7	7	6	6	26
	Not quite true	9	4	9	13	35
	Partly True	43	9	3	16	71
	More true	6	4	3	2	15
	Completely correct	3	0	0	3	6
Total		68	24	21	40	153

Table 8 Symmetric measures

		Value	*Approximate significance*
Nominal by nominal	Phi	0.438	0.003
	Cramer's V	0.253	0.003
No. of valid cases		153	

The Phi value of 0.438 denotes a moderate correlation between the two nominal variables. Similarly, Cramer's V, with a value of 0.253, also indicates a moderate level of association. Both measures exhibit statistical significance, as evidenced by the p-value of 0.003, which falls below the conventional threshold of 0.05. This statistical significance validates that the observed relationship between the age group and ATI range is not a result of random chance, thereby supporting the conclusion that there exists a meaningful association and authentication on pre-treatment and post-treatment between these variables. There are situations which give rise to philosophical and moral discussions because they challenge reality through the depiction, simulating, and falsifying of pictures that want to fall within the empirical category but are unable to do so since they are products of creation rather than empiricism (Greengard, 2019).

Table 9 addresses the question: 'Which of these synonymous terms has the least negative effect on you?'. From this data, 'Artificial Media' is perceived as having the least negative connotation by the highest proportion of respondents (39.2%) and least count is registered in Cl-generated media (13.7%), suggesting it is the most neutral or acceptable term among the given options. The second part addresses the question: 'Which of these synonymous terms do you think best describes the technology?'. The technology referred to as 'Artificial Media' remains the preferred term among respondents, as indicated by 47.1% of participants whereas low response is generated in Synthetic media (11.1%). This finding implies that 'Artificial Media' is not only perceived as the least unfavourable term but also the most precise one. For instance, the story's chronology makes it easy to identify artistic deepfakes of departed cultural icons portraying recent occurrences or commercial efforts (Rodríguez Abellán, 2021).

Table 9 Term preference

	Frequency	*Percentage* (%)
Which of these synonymous terms has the least negative effect on you?		
Deepfakes	46	30.1
Synthetic media	26	17.0
Artificial media	60	39.2
Cl-generated media	21	13.7
Total	153	100.0
Which of these synonymous terms do you think best describes the technology?		
Deepfakes	33	21.6
Synthetic media	17	11.1
Artificial media	72	47.1
Cl-generated media	31	20.3
Total	153	100.0

5 Conclusions

This research provides empirical insight into how consumers interpret and evaluate deepfake advertising within a rapidly evolving digital environment. By analysing responses from 153 participants, the study demonstrates that technological affinity, age, and gender significantly shape perceptions of authenticity, comfort, and trust. Males and younger respondents exhibited higher Affinity for Technology Interaction scores and greater openness toward deepfake-based advertisements, whereas other groups displayed stronger scepticism about realism and ethics.

The findings confirm that terminology influences perception: 'Artificial Media' is viewed as less deceptive than 'Deepfake'. This semantic preference suggests that transparent framing and ethical disclosure can mitigate negative attitudes toward AI-generated marketing content. The results also emphasise the importance of critical thinking education and media literacy to help audiences distinguish between real and synthetic messages.

For advertisers and creative agencies, the study recommends transparent labelling of AI-generated content, informed consent from depicted individuals, and adherence to emerging AI-ethics frameworks. Regulators and policymakers should collaborate with industry bodies to define standards for authenticity verification and disclosure obligations in commercial media.

While limited by its sample size and single-country focus, this study contributes to the global dialogue on responsible AI communication. Future research should examine longitudinal effects of deepfake advertising and cross-cultural variations in ethical judgement. Overall, the research reinforces the necessity for balanced innovation – embracing the creative potential of synthetic media while protecting the moral and informational integrity of the advertising ecosystem.

Conflicts of interest

All authors declare that they have no conflicts of interest.

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