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The Relationship of Digital Literacy, Exposure to AI-Generated Deepfake Videos, and the Ability to Identify Deepfakes in Generation X

Hubungan Literasi Digital, Paparan Video Deepfake yang Dihasilkan AI, dan Kemampuan untuk Mengidentifikasi Deepfake pada Generasi X

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Abstract – The study explores the relationship between digital literacy, exposure to AI-generated deepfake videos, and the ability to identify deepfakes by Generation X in Indonesia who are currently between the ages of 43 and 58. It also analyzes the impact of deepfake identification capabilities on the cognitive, affective, and behavioral aspects of internet users. Through a survey involving 199 respondents taken from a total population of 42 million Generation X internet users in Indonesia, it applied a random sampling method. The sample size was determined by the Slovin formula with a confidence level of 90% and a margin of error of 7.1%. The descriptive analysis shows a moderate level of digital literacy and relatively low exposure to deepfakes. However, the ability to identify deepfakes was found to be low. The results of inferential statistical analysis show that digital literacy and exposure to deepfakes do not have a significant influence on the ability to identify deepfakes. Additionally, the ability to identify deepfakes does not significantly affect cognition, compassion, or behavior. While digital literacy is important, these findings reinforce the assumptions of Generation Theory and Media Dependency Theory. Additionally, it suggests that specific training on media manipulation technologies is needed to improve deepfake detection capabilities. This research implies that efforts to improve digital literacy should be expanded, including technical skills and critical thinking relevant to manipulative media such as deepfakes.

Keywords: deepfake, digital literacy, disinformation detection, Generation X, media exposure

Abstrak *– Studi ini mengeksplorasi hubungan literasi digital, paparan video deepfake yang dihasilkan AI, dan kemampuan untuk mengidentifikasi deepfake oleh Generasi X di Indonesia yang saat ini berusia antara 43 hingga 58 tahun. Penelitian ini juga menganalisis dampak kemampuan identifikasi deepfake pada aspek kognitif, afektif, dan perilaku pengguna internet. Melalui survei yang melibatkan 199 responden yang diambil dari total populasi 42 juta pengguna internet Generasi X di Indonesia, studi ini menggunakan metode sampling acak. Ukuran sampel ditentukan dengan Rumus Slovin dengan tingkat kepercayaan 90% dan margin of error sebesar 7,1%. Analisis deskriptif menunjukkan tingkat literasi digital yang moderat dan paparan deepfake yang relatif rendah. Namun, kemampuan untuk mengidentifikasi deepfake ditemukan rendah. Hasil analisis statistik inferensial menunjukkan bahwa literasi digital dan paparan deepfake tidak memiliki pengaruh yang signifikan terhadap kemampuan mengidentifikasi deepfake. Selain itu, kemampuan untuk mengidentifikasi deepfake tidak secara signifikan memengaruhi kognisi, kasih sayang, atau perilaku. Meskipun literasi digital itu penting, temuan ini menguatkan asumsi Teori Generasi dan Teori Ketergantungan Media. Hasil ini juga menunjukkan bahwa pelatihan khusus tentang teknologi manipulasi media diperlukan untuk meningkatkan kemampuan deteksi deepfake. Penelitian ini menyiratkan bahwa upaya peningkatan literasi digital harus diperluas, termasuk keterampilan teknis dan pemikiran kritis yang relevan dengan media manipulatif seperti deepfakes.*

Kata Kunci: *deepfake, deteksi disinformasi, Generasi X, literasi digital, paparan media*

INTRODUCTION

In the increasingly advanced digital era, Deepfakes technology has become one of the most significant and controversial innovations. It uses deep learning techniques to create or manipulate visual and audio content, resulting in highly realistic yet fake representations (Millière, 2022; Mo et al., 2022). The technology gained widespread attention lately when

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deepfakes videos began popping up on the internet, demonstrating the ability to mimic individual faces and voices with astonishing accuracy, even as if they were doing things they never actually did (Fangming Dai & Li, 2024; Harris, 2021; Shahzad et al., 2022; Tolosana et al., 2020). Behind the benefits of deepfakes in the fields of education, health, economy, creative arts industry, advertising, film production, creative content, and video games that have been felt by its users (Godulla et al., 2021; Li & Wan, 2023; Liu et al., 2019; Malik et al., 2022; Neethirajan, 2021; Prezja et al., 2022; Sivathanu et al., 2023; Vaccari & Chadwick, 2020; Vasist & Krishnan, 2023; Waqas et al., 2022), the capability raises serious concerns regarding privacy, information security, and potential misuse in a variety of contexts, from politics to entertainment (Diakopoulos & Johnson, 2021; Dobber et al., 2021; Federspiel et al., 2023; Vaccari & Chadwick, 2020).

The relevance of deepfakes in modern society cannot be ignored. This technology has penetrated various aspects of daily life. The rapid spread of deepfakes through social media and digital platforms poses significant challenges due to the interconnected nature of online communities and the persuasive power of multimedia content. Deepfakes proliferate across multiple platforms, with interconnected online communities facilitating rapid sharing, even when the initial “infection” rate is low (Xia & Johnson, 2024). The decentralized nature of social media allows personal accounts, rather than automated bots, to be primary spreaders of fake content, including deepfakes (Dourado, 2023). The absence of centralized control mechanisms and the rise of echo chambers contribute to the unchecked spread of deepfakes, necessitating comprehensive strategies for management (Cinelli et al., 2022). While the spread of deepfakes is alarming, some argue that increased awareness and improved reporting mechanisms could mitigate their impact (Eiserbeck et al., 2023; Harris, 2021; Mustak et al., 2023; Tahir et al., 2021). However, the challenge remains significant given the rapid evolution of digital content and user behavior.

Generation X, who was born between 1965 and 1980, has a unique position in the evolution of digital technology. They grew up before the internet age, and witnessed a significant digital technology transition. As a bridge between analog and digital eras, they possess a unique perspective shaped by adapting to emerging technologies while maintaining traditional values and communication methods (Marron, 2015). Although they have adapted to technological advancements, the level of digital literacy among them varies widely (Long et al., 2023) and is lagging behind the younger generation (Guess & Munger, 2023; Lissitsa, 2024). It affects how Generation X processes and assesses digital information and understands emerging technologies like deepfakes.

Exposure to deepfakes generated by AI has become a significant threat to the integrity of digital information, especially for Generation X. With their unique technological experience, they face special challenges in navigating an increasingly complex digital environment vulnerable to exploitation by irresponsible parties to spread false content. Research highlighting the impact of exposure to deepfakes on Generation X is still limited, especially in the context of how digital literacy affects their ability to recognize and respond to such content.

This current study aims to provide an understanding of the interaction between exposure to deepfakes and digital literacy among Generation X. It will investigate the impact of digital literacy levels, digital literacy training, frequency of internet use, and exposure to deepfakes on Generation X’s ability to identify deepfakes, and how it affects cognitive and affective processes, as well as behavioral responses. This research will provide a deeper insight into the relationship between technology and the digital critical abilities of Generation X in the modern information era.

Gap Analysis

Research on the impact of deepfakes technology has grown rapidly in recent years, with a primary focus on technology development, detection, and ethical implications (Chen et al., 2023; Diakopoulos & Johnson, 2021; Fosco et al., 2022; Ismail et al., 2022; Lu et al., 2023; Naskar et al., 2024; Patel et al., 2023; Trinh et al., 2021; Xiao et al., 2023; Yang et al., 2023; Zhao et al., 2023). Previous studies have underscored the potential dangers of deepfakes, especially in the context of the spread of disinformation and manipulation of public opinion (Caldwell et al., 2020; Hameleers et al., 2022; Nieweglowska et al., 2023; Shahzad et al., 2022). However, most of the existing literature tends to focus on the general impact on society or on younger generations, such as Generation Z and millennials, who are more active in the use of digital media and the latest technology (Ameen et al., 2023; Blancaflor et al., 2023, 2023; Hancock &

Bailenson, 2021; Karpinska-Krakowiak & Eisend, 2024; Shin & Lee, 2022; Van Der Sloot & Wagensveld, 2022). Generation X, which has unique characteristics in the use of technology and digital literacy, still receives less attention in this field of study. The lack of empirical data on how digital literacy affects the perception and actions of Generation X toward deepfakes creates a significant gap in the existing literature.

The current research offers an innovative and significant contribution to the literature on deepfake and digital literacy, with a particular focus on Generation X. The novelty aspect of this research lies in its unique population. Generation X, is often overlooked in the study of digital technology. Different from Generation Z or millennials, Generation X faces unique challenges in understanding modern technology due to their limited experience with technology during their youth. This study closes the gap in literature by exploring the relationship between Generation X's digital literacy and their ability to recognize deepfakes. Practically, the results of this study are expected to provide a basis for more targeted digital literacy initiatives, thereby improving the ability of Generation X to navigate an increasingly complex digital environment. It will be one of the first to specifically explore how this generation faces the challenges of Deepfake. The focus on Generation X provides a fresh perspective and enriches the literature with new data and insights.

Digital Literacy and Deepfake

The connection between digital literacy levels and the ability to identify deepfakes content is important in the era where the proliferation of synthetic media poses a significant challenge to information integrity. Digital literacy includes a wide range of skills in the use of digital technology. The literature shows that individuals with higher media literacy are better equipped to distinguish the authenticity of digital content, thereby reducing the potential for misinformation and manipulation (Goh, 2024; Hameleers et al., 2024).

Several studies have shown that media literacy improves the ability of internet users to evaluate the credibility of information sources and the motivations behind media production. For instance, Hameleers et al., (2024) found that individuals who engage in argument-based reasoning are more likely to accurately identify political deepfakes, suggesting that critical thinking skills fostered by media literacy can mitigate the impact of deceptive content. Goh, (2024) recommends digital literacy programs to improve identification performance in real-world contexts, where contextual clues may not be available. Educational initiatives are needed to equip individuals with the skills to navigate the complexities of digital media.

Twomey et al., (2023) argue that cultivating deepfake literacy and skepticism can protect individuals from the adverse effects of misinformation. It is in line with the findings of McCosker, (2022) who suggested increasing digital literacy as a preventive measure against the risks posed by deepfakes, especially in social media environments where such content is considered prevalent.

H1: There is a significant influence of digital literacy on the ability to identify deepfakes.

H2: There is a positive relationship between participation in digital literacy training and the ability to identify deepfakes

Frequency of Internet Use

The psychological aspects of frequent internet usage play a significant role in deepfakes recognition. Users who frequently navigate online environments may develop cognitive heuristics that aid in identifying inconsistencies in media. For example, Barari et al., (2024) found that individuals exposed to deepfakes in controlled environments displayed varying levels of skepticism based on their prior experiences with digital media, suggesting that broad literacy in politics and digital technology enhances discernment between deepfakes and authentic videos.

However, it is important to realize that while frequent internet use can improve content identification capabilities, it may also lead to desensitization. When users are overwhelmed by the volume of content they are dealing with, the capacity to critically evaluate each piece of content is reduced. Vaccari & Chadwick, (2020) highlight that deepfakes are more likely to create uncertainty than outright fraud. This uncertainty tends to be felt more by users who consume media more often, because they are no longer able to scrutinize content due to the amount of information they have to process every day.

The relationship between the frequency of internet use and the amount of exposure to deepfakes can be influenced by various factors, including user engagement with digital content, and the proliferation of deepfake technology on various social media platforms. As internet usage increases, the likelihood of finding deepfake content also increases. The integration of deepfakes into everyday culture, especially on social media platforms, is further normalizing their presence (McCosker, 2022).

Research indicates that users who spend more time on social media demonstrate improved performance in detecting deepfakes, especially when familiar faces are involved (Nas & De Kleijn, 2024). This suggests that frequent exposure to digital content may enhance users' critical skills in identifying manipulated media.

H3: There is a relationship between the frequency of internet use and the number of deepfakes exposures.

H4: There is a significant influence of the number of deepfakes exposures on the ability to recognize deepfakes.

Deepfakes Impact on the Internet Users

Research indicates that deepfakes can alter perception and emotional processing, leading to a dampened response to AI-generated content. Deepfakes can impair emotional evaluations, particularly with positive expressions, leading to slower and less favorable assessments (Eiserbeck et al., 2023). Furthermore, users may develop harmful psychological associations with deepfakes content, even if they do not believe it to be true (Harris, 2021).

Individuals often misjudge the accuracy of deepfakes claims, particularly when informative cues are absent, which can increase the likelihood of sharing such content. Frequent internet users are more susceptible to sharing deepfakes, especially when they perceive the content as credible due to a lack of informative cues. Cognitive ability also plays a role; those with higher cognitive skills may be more skeptical of deepfakes when provided with context, yet can be misled in the absence of such cues (Ahmed, 2021). The digital environment has a role in shaping internet user's cognition, influencing how they process and respond to the information (Schmitt & Woolf, 2018).

Cognitive flexibility is important in deepfake detection. Research shows that individuals with lower cognitive abilities may struggle more with deepfake detection (Ahmed, 2023). This discrepancy can lead to a heightened vulnerability to misinformation, particularly among users who are less adept at critical thinking. Furthermore, the emotional implications of encountering deepfakes can exacerbate cognitive biases, leading individuals to accept fabricated content that aligns with their pre-existing beliefs (Qureshi & Khan, 2024). This phenomenon is particularly evident in politically charged contexts, where individuals may be more inclined to believe deepfakes that support their ideological views, thereby reinforcing existing biases and potentially skewing political attitudes (Dobber et al., 2021).

Moreover, the psychological impact of deepfakes extends to social media behaviors. Users share content, including deepfakes, without verifying its authenticity due to the fear of missing out and deficient of self-regulation (Ahmed et al., 2023). This behavior is exacerbated by the emotional appeal of deepfakes which can create a strong incentive for users to engage. The interplay between emotional responses and cognitive processing is critical, as users may prioritize emotional gratification over rational evaluation, leading to the spread of misinformation (Li & Wan, 2023).

The implications of deepfakes are not limited to individual cognition, but also affect collective behavior in social networks. The normalization of deepfakes in various domains, including advertising and political discourse, raises concerns about the potential manipulation of public opinion and erosion of democratic processes (Qureshi & Khan, 2024).

H5: There is a significant influence of the ability to identify deepfakes on internet users' cognition.

H6: There is a significant influence of the ability to identify deepfakes on the internet users' affection.

H7: There is a significant influence of the ability to identify deepfakes on internet users' behavior.

METHOD

The current research uses a quantitative approach. The study started by creating research tools in the shape of questionnaires to collect data related to the hypothesis being tested. Several ended questions and a Likert scale were used to gauge variables, like Internet usage frequency and Digital Literacy. Digital Literacy encompasses skills such, as using tools and assessing the credibility of online information (Law et al., 2018) which were assessed using the Likert scale. Respondents were tasked with determining the authenticity of a set of deepfake videos to evaluate their ability to spot content accurately on the internet. They also shared how frequently they come across deepfake content using a Likert scale to gauge their exposure, to media. Additionally, it measured how deepfake videos affect internet users thoughts and feelings by examining shifts, in their perceptions and actions after viewing content through the Likert scale.

Data was obtained by survey, carried out from June to August 2024 with a simple random sampling technique to ensure representativeness. Using the Slovin Formula (1), with the confidence level 90% and the margin of error of 7.1%, the target sample was 199 respondents from Generation X in Indonesia who actively use the internet to get statistically significant results. APJI, the Indonesian internet service provider association, released that the population of Generation X amounted to 18.98% of the 221.56 million internet users in Indonesia. Furthermore, the data was analyzed with descriptive statistics to describe the distribution of answers, and inferential statistics to test the significance of the relationship between the variables studied. Julius AI was utilized to do the a statistical analysis since it is able to do perform relevant analysis according to the data characteristics (Khan, 2024).

$$n = \frac{N}{1+N(e)^2} \quad \text{..(1)}$$

$$n = \frac{42.052.088}{1 + 42.052.088(0.071)^2}$$

$$n = 198.37$$

Remarks:
n = Sample
N = Population
e = Margin of errors

Theoretical Framework

This research is based on the integration of two main theories: Prensky's Generation Theory and DeFleur and Ball-Rokeach's Media Dependency Theory, to understand how Generation X responds to the deepfake phenomenon in the context of information technology.

Prensky, (2001) divides generations based on their relationship with digital technologies: digital natives, and digital immigrants Generation X, who was born between 1965 and 1980, falls into the category of digital immigrants, as they grew up in the era of analog technology and only adapted to digital technology in adulthood. These experiences affect how they leverage, understand, and respond to information technology, including their ability to recognize and assess the authenticity of digital content, such as deepfakes.

As digital immigrants, Generation X faces challenges in adopting new technologies. This can lead to technological fatigue (technostress) and limitations in digital literacy skills, which ultimately affects their ability to recognize visual manipulation such as deepfakes. This generation is more dependent on past experiences, so it is slower to adapt to complex or manipulative digital content than the generation born in the digital era.

The Media Dependency Theory of DeFleur and Ball-Rokeach (1976) emphasizes that social characteristics such as age, experience, and education level shape media consumption patterns and individual responses to information. Generation X, as a social category, has a different media consumption pattern from other generations. They are more likely to trust traditional media, such as television and newspapers, compared to digital media. However, the growing exposure to digital content, including deepfakes, has created new challenges in filtering valid information from the manipulative.

Picture 1 Correlation Matrix

This theory helps explain that Generation X as a social group has homogeneous characteristics in terms of, i.e. digital literacy levels vary, but tend to be lower than those growing up in the digital age; and Susceptibility to information manipulation, as they often do not have a digital experience deep enough to distinguish genuine content from fake content.

Results and Discussion

The Effect of Digital Literacy and Digital Literacy Training on Deepfakes Identification Ability

The results of the analysis (Table 1) show that the digital literacy level of the respondents is at a moderate level (Mean = 2.78, Std = 0.54), while their average ability to identify deepfakes tends to be low (Mean =

1.80, Std = 0.78). In the descriptive analysis (Picture 1), a moderate positive correlation between the two variables was seen (r = 0.39). These results provide an early indication that digital literacy may have an important role in helping individuals detect deepfakes. However, the results of the inferential analysis (Table 2), do not support the H1 hypothesis, with an insignificant p-value (p = 0.5498) and a very small regression coefficient value (β = 0.0546). A negative R-squared value (-0.1275) also indicates that this model cannot adequately explain the relationship between digital literacy and deepfakes identification ability.

Table 1 Descriptive Statistics

	Digital Literacy	Internet use frequency	Deepfakes Exposure	Ability to identify deepfakes	Cognition	Affection	Behavior
N	200	200	200	200	200	200	200
mean	2.78	2.88	2.22	1.80	3.11	3.75	2.13
std	0.54	1.55	1.13	0.78	0.55	0.69	1.24
min	1.50	1.00	1.00	0.00	1.75	2.25	0.50
25%	2.33	1.00	1.00	1.33	2.75	3.50	1.00
50%	2.75	2.00	2.00	1.67	3.25	4.00	2.00
75%	3.17	4.00	3.00	2.33	3.50	4.25	3.00
max	4.17	5.00	4.00	3.67	4.50	5.00	4.50

H2 analysis also yielded a result where taking part in literacy training did not seem to have a strong correlation, with being able to detect deepfake videos effectively. Although there was a variation in scores, between those who underwent training and those who didn't the T test results indicated that this difference was not statistically significant (t=. 0.3980, p= 691). The slight effect size (Cohen's d = 0.0563), with a point biserial correlation (correlation coefficient rpb = 0.00283) adds weight to the argument that existing digital literacy programs have only a minor influence on Generation X's proficiency, in detecting deepfake content.

The results align, with research indicating that having skills in general is linked to ones comprehension and utilization of technology (Cetindamar et al., 2024; Tinmaz et al., 2022). However, these skills may not encompass abilities like detecting deepfake content that mandate know how and a profound grasp of manipulative media techniques. Conventional digital literacy instruction often concentrates on proficiencies such as cybersecurity or adeptly accessing information efficiently. May not adequately equip people to navigate intricately manipulated material, like deepfake videos. According to research conducted by Vaccari & Chadwick, (2020) suggests that just providing literacy training may not be sufficient to address the issues presented by manipulative technology.

The Connection Between How Someone Uses the Internet and Their Exposure, to Deepfake Content; How This Affects the Ability to Detect Deepfake Videos.

According to the findings, from the analysis conducted on Generation X respondents internet usage patterns and exposure to deepfake content indicate that their internet usage frequency falls within a range (Mean = 2.88, Std 1.55). In terms of exposure to deepfake content specifically among this group is mostly low to frequent (Mean = 2.22, Std = 1.13). Additionally depicted is a link, between how often individuals use the internet and their encounters with deepfake content (r=0.22). This indicates that there is a possibility that the more often individuals use the internet, the greater their potential for exposure to deepfakes.

Table 2 Inferential Analysis Results

Metiric	H1	H2	H3	H4	H5	H6	H7
Pearson Correlation	0.0425			0.0305	-0.0172	0.0116	0.1121
Correlation p-value	0.5498			0.6683	0.8093	0.8708	0.1139
R-squared	-0.1275			-0.1157	-0.0268	-0.0001	-0.0134
MSE	0.6076			0.6013	0.2533	0.3938	1.3997
Regression Coefficient	0.0546			0.0329	0.0203	-0.0003	0.1512
Intercept	1.7542			1.7542	3.1047	3.7469	2.1531
F-statistic	-4.2974			-3.9414	-0.9905	-0.0035	-0.5038
F-statistic p-value	1.0000			1.0000	1.0000	1.0000	1.0000
T-statistic		-0.398					
T-statistic P-value		0.691					
Cohen's d		0.0563					
Point-biserial correlation		0.0283					
Spearman Correlation			-0.05				
Correlation p-value			0.4819				
ANOVA F-statistic			0.1832				
ANOVA p-value			0.9078				
Eta-squared			0.0028				

However, the results of inferential analysis provide a different picture. For H3, the Spearman correlation was not significant (ρ = -0.0500, p = 0.4819), and the ANOVA results also did not support a meaningful relationship between the frequency of internet use and deepfakes exposure (F = 0.1832, p = 0.9078). In addition, a very small eta-squared value ($\eta^2 = 0.0028$)

suggests that internet use contribute for only a small portion of the variation in deepfake exposure. The empirical data in the current research do not support the hypothesis of a theoretical expectation that more time spent on the internet will increase the likelihood that individuals will be exposed to deepfake content.

Hypothesis H4 assumes that the amount of exposure to deepfakes affects Generation X's ability to identify deepfakes. Preliminary descriptive results do show a moderate correlation between deepfakes exposure and the ability to recognize them ($r = 0.33$), which essentially supports this hypothesis. However, the inferential results again do not support this conclusion. Pearson's correlation between deepfakes exposure and identification ability was very low and insignificant ($r = 0.0305$, $p = 0.6683$), with a negative R-squared value (-0.1157), which suggests that the regression model cannot explain the variability of deepfakes identification ability based on deepfakes exposure.

These results suggest that while the initial assumption in the literature—that increased exposure to manipulative content can improve an individual's ability to recognize it—seems plausible (Chadwick & Stanyer, 2022), this context may not be fully applicable to Generation X. One possible explanation is that Generation X may not have enough skills or knowledge to identify deepfakes, even though they are frequently exposed to such content. This is consistent with previous research that shows that exposure alone is not enough to improve detection capabilities without adequate media knowledge or literacy (Burnham & Arbeit, 2023).

In addition, the low exposure to deepfakes among Generation X respondents (Mean = 2.22) may also explain why this hypothesis is not supported. If respondents are rarely exposed to deepfake content, they may not have developed a sensitivity to the visual or narrative traits that are typical of manipulative content. Research by Ienca, (2023) and Lorenz-Spreen et al., (2021) show that individuals who interact more often with manipulated digital media will be more skilled at identifying manipulative characteristics such as deepfakes. However, in the case of Generation X, even though they use the internet with enough frequency, deepfakes content may not be a big part of their digital experience yet.

The Effect of Deepfake Identification Ability on Cognitive, Affective, and Behavioral Aspects of Internet Users

The Analysis results showed that Generation X had a relatively low ability to identify deepfakes (Mean = 1.80, Std = 0.78). Affective impact of deepfakes was the highest among the impacts measured (Mean = 3.75, Std = 0.69), followed by cognitive impact (Mean = 3.11, Std = 0.55), and behavioral impact was the lowest (Mean = 2.13, Std = 1.24). However, the results of inferential analysis show that the relationship between the ability to identify deepfakes and these three aspects is not statistically significant.

For H5, which assumes that deepfakes identification ability affects cognitive aspects, inferential analysis showed a very low and insignificant correlation ($r = -0.0172$, $p = 0.8093$). In addition, a negative R-squared value (-0.0268) and a low regression coefficient ($\beta = 0.0203$) indicate that the model is unable to explain the significant influence of identification ability on cognitive impact. These findings suggest that, despite the literature stating that awareness of manipulative content can affect individual cognitive processing (Schmitt & Woolf, 2018), the empirical data from the current research do not support any significant influence on Generation X. This may be due to the low level of media literacy among respondents, so they are not yet fully able to understand or critically analyze manipulative information.

For H6, which proposed a significant influence of deepfakes identification ability on affective aspects, the results showed a similar pattern. Pearson's correlation between deepfakes identification ability and affective impact was very small ($r = 0.0116$, $p = 0.8708$), with an almost zero R-squared (-0.0001). This indicates that an individual's ability to recognize deepfakes does not have a significant effect on their emotional reactions. Interestingly, although the affective impact on deepfakes was recorded as the highest in the study, the ability to identify did not play a major role in modifying those emotional responses. Emotional reactions may be more influenced by other factors such as engagement with content, trust in information sources, or a level of critical awareness of the media (Twomey et al., 2023).

H7 tested the influence of deepfakes identification ability on internet user behavior. Although the descriptive analysis showed that the behavioral impact was the lowest among the three aspects tested (Mean = 2.13, Std = 1.24), the inferential results also showed that there was no significant influence of deepfakes identification capabilities on behavior. Pearson's correlation ($r = 0.1121$, $p = 0.1139$) and negative R-squared value (-0.0134) indicate that the regression model is not able to explain the variability of behavior based on the ability to identify deepfakes. These results are in line with previous research that shows that while individuals can be aware that content has been manipulated, this does not necessarily lead to significant behavioral changes (MacLean et al., 2024). Factors such as internet usage habits, motivation for accessing information, and social media orientation seem to influence behavior more than the technical ability to detect deepfakes content (Ahmed, 2023; Lorenz-Spreen et al., 2020).

These findings suggest that while the ability to identify deepfakes is expected to influence cognitive processing, affective reactions, and behavior, empirical data do not support the hypothesis in Generation X. Some possible explanations are that Generation X, despite having sufficient internet exposure, does not yet have the level of visual and technical literacy necessary to effectively process and react to manipulative content such as deepfake. In addition, the low ability to identify deepfakes among respondents indicates that more in-depth education and training related to media literacy is urgently needed to increase their resilience to manipulated digital content.

The current research has important theoretical implications related to digital literacy and its impact on deepfake detection. Although digital literacy is considered an important factor in the ability to identify manipulative content, the results of The current research suggest that digital literacy in general may not include the skills needed to recognize deepfakes. This suggests that digital literacy theory needs to be expanded to include more specific technical skills, including an understanding of deepfakes technology and relevant detection tools. The study also proposes that passive exposure to the internet and manipulative content is not enough to improve identification skills, which enriches theories related to media exposure and active learning.

In addition, the results showed the absence of a significant influence of deepfake detection capabilities on cognition, affection, and assumption-challenging behavior in theoretical models that correlate technical skills with psychological and behavioral changes. It suggests that technical ability is not enough to influence information processing or emotional responses and that factors such as social context and critical awareness need to be taken into account in the theory of media psychology. These findings could prompt revisions to existing theoretical models and open up opportunities for further research into the emotional and behavioral impacts of digital disinformation.

Furthermore, although the relationship between the variables in the study is not statistically significant, some practical implications need to be considered. First, the digital literacy program needs to focus on the specific recognition and detection of deepfake content. Simulation-based and interactive education may help improve relevant technical abilities, given that general digital literacy is not enough to identify deepfakes. Second, passive exposure to deepfakes through the use of the internet does not improve detection capabilities. Therefore, structured educational programs, especially those that focus on critical skills in recognizing media manipulation, are indispensable. In addition, since the ability to identify deepfakes does not show a significant effect on cognition, education should place more emphasis on critical thinking skills and in-depth evaluation of information, rather than just the technical aspects of media detection.

The results of the current research show that Generation X is more vulnerable to the emotional impact of deepfakes. Therefore, digital literacy programs should include training to manage affective responses and build emotional resilience to disinformation that exploits emotional aspects. In the behavioral aspect, the ability to recognize deepfakes has no significant influence. It demands a broader approach, including digital ethics education and social responsibility to drive more tangible behavioural change in the face of disinformation such as deepfakes.

From a behavioral theory perspective, this result can be attributed to the low level of digital literacy of Generation X as digital immigrants, as Prensky, (2001) explains. Their ability to recognize and analyze deepfake content is limited, so exposure to this phenomenon does not result in a significant response at the cognitive, affective, or behavioral levels. This also supports previous findings that the digital literacy training applied has only a small effect on their ability to identify deepfakes.

According to the Media Dependency Theory (Ball-Rokeach & DeFleur, 1976), Generation X as a social category has a response pattern that tends to be homogeneous to media information. Based on the results of the study, it can be explained that the social characteristics of Generation X, such as their past experiences with analog media and slow adaptation to digital technology, form a uniform pattern of behavior. Exposure to deepfakes is not strong enough to trigger significant differences in responses due to their limitations in understanding or utilizing information technology critically.

CONCLUSION

The current research explores the influence of digital literacy, exposure to deepfakes, and the ability to identify deepfakes in Generation X, as well as their impact on cognition, affection, and behavior. Although some descriptive findings provide preliminary support for the hypothesis, the results of the inferential analysis suggest that most of the hypothesized relationships are not statistically significant. Digital literacy (H1), with correlation value 0.5498, and Digital Literacy Training (H2), with T-value -0.3980, did not show a significant influence on the ability to identify deepfakes. Internet exposure (H3), with correlation value 0.4819, and the deepfakes exposures (H4), with correlation value 0.6683, did not significantly improve those abilities. Furthermore, the ability to identify deepfakes does not exert a significant influence on the cognitive (correlation value 0.8093) affective (correlation value 0.8708), or behavioral aspects of the user (correlation value 0.1139).

Collaboration between policymakers, educators, and digital platforms needs to be improved to design more effective and targeted interventions. Digital literacy education must include technical, emotional, and ethical aspects, to improve the ability of Generation X to deal with disinformation and manipulative content such as deepfakes. Wider and more accessible campaigns, as well as the integration of deepfake detection technology by social media platforms, can help strengthen people's resilience to future deepfakes threats.

For future research, several areas need to be expanded and further studied. First, a more in-depth study of the relationship between specific digital literacy (including specialized training in deepfakes detection) and the ability to identify manipulative content is urgently needed. Further research also needs to consider social and contextual factors, such as the impact of digital culture or the influence of social groups in spreading disinformation. In addition, researchers can examine the role of psychological factors, such as confidence levels or digital skepticism, that may moderate the relationship between digital literacy and deepfake detection. Thus, further research is expected to expand the scope of digital literacy and provide more comprehensive solutions to deal with disinformation in the digital era.

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