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Information priming for resilience: strengthening belief systems in the age of deepfakes

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Abstract

Introduction. As artificial intelligence advances, deepfakes have emerged as a major cybersecurity threat. Most existing research emphasises perception or algorithmic development, leaving limited understanding of how to strengthen individuals' ability to discern truth from deception and avoid victimisation. This study investigated priming effects in deepfake detection through media richness theory and dual processing theory and proposes a framework for enhancing detection strategies.

Method. The experiment adopted a mixed design, with priming effect as a between-subjects factor across text, image, and multimedia modalities with embedded ground truth. Participants were assigned to the control, conceptual priming, and perceptual priming groups. Both subjective and objective data were collected to evaluate participants' perceptions and detection performance.

Analysis. Descriptive analyses examined deepfake detection accuracy and reaction time. Qualitative questions explored participants' perceptions of deepfake detection, prior experiences, and reflections.

Results. Multimedia provided rich cues that supported faster judgments, whereas lean media content demanded longer analysis. Conceptual priming promoted intuitive processes and encouraged deliberate detection strategies, while perceptual priming engaged reflective systems and heightened sensitivity to anomalies.

Conclusion(s). Information priming offers a practical approach to supporting users in distinguishing authenticity from deepfakes. Perceptual priming was more effective than conceptual priming, particularly when detecting manipulations in multimedia.

Introduction

In 2024, a deepfake video of UK politician Nigel Farage appearing in a campaign livestream while playing Minecraft was widespread (Waterson, 2024). This video clip went viral, sparking confusion and amusement online. The case has raised concerns that deepfake technology could distort political discourse and erode public trust. In the same year, the National Association of State Chief Information Officers identified deepfakes as the top cybersecurity threat. *Deepfakes*, refer to highly realistic media content generated by deep neural networks designed to deceive audiences into perceiving them as authentic (Mirsky & Lee, 2021). The most common deepfakes are photos and videos with facial or body replacement and audio with voice substitution. Deepfakes use generative adversarial networks, in which two neural networks compete; one generates fake content while the other evaluates the authenticity of the samples to be real or fake. This adversarial process trains both models iteratively to produce increasingly realistic content (Westerlund, 2019). Such advancements challenge the authenticity verification of online information, especially when exploited for financial fraud and political disinformation (Lohrmann, 2024).

In computer-mediated communication, individuals generally rely on linguistic cues to detect deception (Ho, Hancock, Booth, & Liu, 2016). However, deepfakes manipulate multiple modalities (Rana et al., 2022), making them more difficult to identify. Human detection accuracy averages only 52%, close to random guessing (Boutadjine et al., 2025). People also tend to mistake deepfakes for authentic events and frequently overestimate their ability to detect them (Köbis et al., 2021), including those with technical or cybersecurity expertise (Sütterlin et al., 2022).

Deepfakes are particularly persuasive because they provide multimedia cues that easily mislead (Vaccari & Chadwick, 2020). This effect can be reinforced by priming, in which exposure to certain information influences how information is perceived and interpreted (Higgins et al., 1985). Priming has been shown to be effective in encouraging more deliberate search behaviors, such as verifying multiple sources (Yamamoto & Yamamoto, 2018). It may therefore enhance individuals' ability to detect deepfakes and critically evaluate digital content.

Although priming research in psychology is extensive (Pickering & Ferreira, 2008; Schacter & Buckner, 1998), and many studies have examined human perception or AI algorithms for deepfake detection (Korshunov & Marcel, 2020; Somoray & Miller, 2023), little work has explicitly applied priming to improve deepfake detection. Therefore, we assume that individuals exposed to certain primes are more likely to spot the manipulated part of deepfake content. This research investigates how information priming cues can be designed to enhance human efficiency and reflection in detecting multimedia deepfakes.

Study framework

Our study proposes a framework that illustrates how information priming shapes individuals' interactions with multimedia deepfakes. This framework is grounded in media richness theory and dual process theory.

Media richness theory

Media richness theory explains effective communication depends on the richness of the selected medium relative to the unclear tasks. *Information richness* is defined as the capability to modify a recipient's interpretation within a given time interval (Daft & Lengel, 1986). Daft and Lengel also suggested that information rich communication is behavior capable of promptly clarifying ambiguities to alter understanding. Rich media facilitate quicker decision making by offering multiple communication cues and providing interpretative feedback, thus helping to resolve uncertainty more efficiently (Dennis & Kinney, 1998). Conversely, lean media offer fewer cues and slower feedback, limiting message clarification and delaying decision making. It is only suitable for unequivocal tasks that are clearly based on facts.

Richness criteria include multiple cues, linguistic diversity, and personal attention (Daft et al., 1987). Rich media enhances the perceived richness of information. Moreover, a more enriched online learning environment can reduce anxiety and increase learning enjoyment (Ishii et al., 2019). Increased or diversified cues in emerging media technologies can positively influence user experience and interaction (Xu & Liao, 2020). Richness cues not only facilitate learning but also enhance individuals' capacity to detect deception. In computer-mediated environments, the richness of cues enables recipients to adopt a more critical stance toward the received message, thus enhancing the accuracy of information interpretation and deception detection capabilities (Ho, Hancock, Booth, Liu, et al., 2016).

Rich media	Lean media
More cues	Less cues
Equivocal tasks (ambiguous, interpretative)	Unequivocal tasks (clear, fact-based)

Table 1. Media richness theory.

Dual process theory

Tversky and Kahneman (1974) described how people rely on heuristic principles when making judgments under uncertainty. For example, the representativeness heuristic describes the tendency for people to judge how likely something is based on how much it seems to fit a general category or pattern. The availability heuristic means people estimate how likely something is based on how quickly they can think of examples (Tversky & Kahneman, 1974). Later, the representativeness and availability heuristics were expanded into dual process theory, distinguishing between an intuitive system (System 1) and a reflective system (System 2; Kahneman & Frederick, 2002). Kahneman and Frederick classified System 1 as fast, intuitive, and affective, and System 2 as slow, deliberative, and neutral. In the dual process model, System 1 quickly proposes intuitive answers, while System 2 monitors the quality of these proposals. Decision errors or biases arise when System 2 fails to monitor the quick, often flawed judgments produced by System1 (Kahneman & Frederick, 2002).

Dual process models have been applied across many fields to categorise human cognitive processes (Carlston, 2013). Based on the operational patterns of human cognition, dual process models can be categorised into automatic processing and controlled processing. This model can be used to explore deeply the factors influencing people's intuitive and deliberate judgments (Glöckner & Witteman, 2010). It has been applied to the construction of mathematical models for medical decision making (Djulbegovic et al., 2012) and ethical decision making (Warner et al., 2024).

Priming effect is often explained through dual process theory. This framework describes automatic processing as enhancing familiarity through activation or associative priming, while controlled, conscious processing involves strategic evaluation. It has been used to examine lexical priming and recognition (Mandler et al., 1990), the interaction between automatic activation and expectancy strategies in semantic priming (Mummery et al., 1999), and influences on semantic coherence judgments (Sweklej & Balas, 2024).

Intuitive system (system 1)	Reflective system (system 2)
Fast	Slow
Instinctive	Deliberative
Affective	Neutral

Table 2. Dual process theory.

Information priming

The framework considers two types of priming cues: conceptual priming that activates semantic associated processing and perceptual priming that focuses on form-based stimuli. These cues influence people's judgments of different deepfake media. When deepfakes are presented as lean media, conceptual priming aligns with the reflective system, requiring more time for analytical processing. In contrast, deepfakes are presented as rich media, and perceptual priming activates the intuitive system, prompting rapid judgments. The integration of media richness theory and dual process theory explains how different media content and priming mechanisms affect participants' detection time, reflection, and interpretation. This information priming framework contributes to the advancement of effective strategies for deepfake detection.

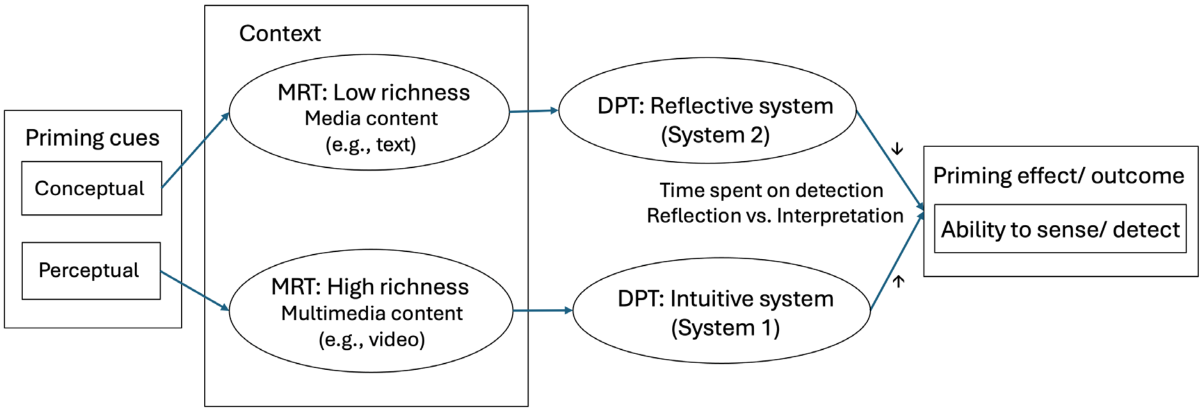

Figure 1. Information priming framework.

Priming effect

The priming effect refers to the way that exposure to stimuli influences subsequent thought and behavior (Higgins et al., 1985). People's categorisation of new information is influenced by memory traces prior to stimuli. When facing uncertainties, individuals may rely on recently encountered information as heuristic guidance (Higgins et al., 1985). When individuals search for information, their attention is directed not only by knowledge stored in memory but also by the relative salience of cues in the environment (Higgins, 1996). Consequently, people are more likely to rely on recently encountered or salient information as a cognitive shortcut for categorisation.

Priming has been widely applied in both education and human-computer interaction. For example, subliminal cues as triggers in digital interactive interfaces can enhance learning outcomes (Chalfoun & Frasson, 2008, 2011). Cognitive psychology distinguishes between two main forms of priming: (a) perceptual priming, which depends on perceptual stimuli and (b) conceptual priming, which depends on conceptual associations. Perceptual priming happens before semantic processing, making stimuli easier to recognise in subsequent encounters. In contrast, conceptual priming enhances conceptual fluency, making stimuli easier to retrieve from memory (Lee, 2002). Qin et al. (2016) explored the perceptual and conceptual priming effect on consumers' evaluations of copycat brands in marketing. They discussed perceptual similarity focuses on surface-level similarities, such as spelling, typography, or pronunciation. Conceptual refers to semantic meaning or brand associations, encompassing deeper similarities (Qin et al., 2016). Copycat brands may adopt names similar to those of well-known brands to evoke perceptual similarity or names with similar meanings to evoke conceptual similarity.

Perceptual priming and conceptual priming differ in the cognitive systems engaged and the level of information processing facilitated. Perceptual priming depends on sensory features, such as visual or auditory similarity, limiting its effectiveness to recognition and form-based tasks rather than semantic comprehension (Schacter, 1992; Wiggs & Martin, 1998). As a multidimensional construct, perceptual priming encompasses visual and auditory components, each linked to its corresponding formal system. Compared to older adults, young adults exhibit stronger priming effects, particularly on perceptual tests. When encoding with perceptual processing, young adults demonstrate significantly greater priming on task match encoding and testing procedures (Ward, 2023). On the other hand, conceptual priming grounded in the semantic system enhances the accessibility of meaning-based stimuli. It more effectively supports tasks involving comprehension, creativity, and semantic judgment (Dennis et al., 2013; Woltz, 1996). Conceptual priming can significantly enhance learners' linguistic recognition and sentence comprehension performance, particularly improving language proficiency (Khaghaninejad, 2024).

Perceptual priming	Conceptual priming
Form-based stimuli	Meaning-based stimuli
Sensory features (visual, auditory)	Semantic associations
Example: video	Example: text

Table 3. Conceptual vs. perceptual priming.

Research design

This study employed a between-subjects experimental design to compare conceptual priming and perceptual priming in human deepfake detection through media richness theory and dual process theory. Text, visual, and multimedia modalities were set up as different deepfake tasks. Participants completed deepfake detection tasks under three conditions: (a) control group: received a news article about deepfake technology, (2) conceptual priming: received a text-based introduction with deepfake detection strategies, and (3) perceptual priming: received and watched a video introduction to deepfakes. Tasks included identifying manipulated versus authentic news articles, images, and videos. The study Institutional Review Board approval was obtained from Florida State University.

Participants

We recruited 28 university students (11 males, 39%, and 17 females, 61%) as they represented a primary population of digital media consumers and demonstrated sufficient familiarity with deepfakes-related tasks. All participants provided informed consent before taking part in the research.

Procedure

Participants were first asked to complete a baseline detection test via a Qualtrics with a mix of deepfakes as part of the test. They were asked to judge the authenticity of the content without prior instruction. Afterward, participants were randomly assigned to one of three priming conditions (control, conceptual, or perceptual). The control group received a news article about deepfake technology, ensuring their reading time was comparable to the other two groups. The conceptual priming group received an introduction to deepfakes, including strategies for effective detection. The perceptual priming group watched a video introduction to deepfakes. Participants were required to answer a single choice question indicating the priming condition they received, serving as a manipulation check. Afterward, they proceeded to the manipulated digital content test that included news articles (textual tasks), images (visual tasks), and multimedia content (multimedia tasks). Each content type included two sets of manipulated materials and two sets of authentic materials. Participants were then asked to judge the content and to rate their confidence, with reaction time for each trial recorded. Finally, they answered 13 open-ended questions, reflecting on their perceptions and experiences of detecting deepfakes across different modalities.

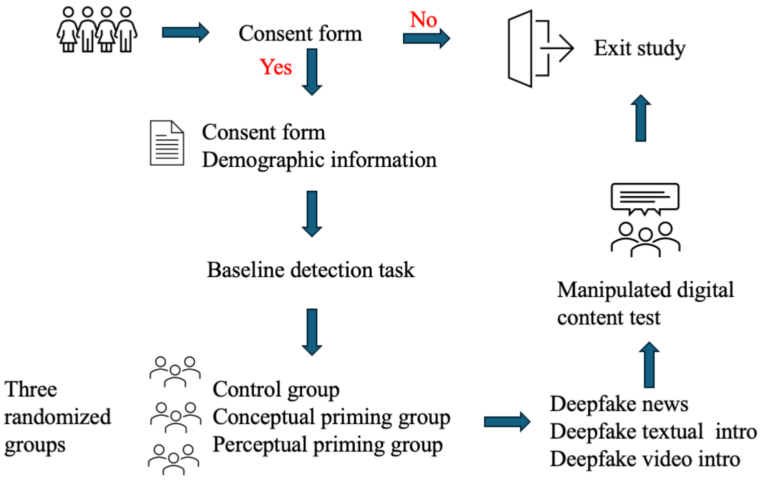

Figure 2. Experimental design.

Data analysis

We employed both descriptive and qualitative analyses to examine participant responses.

Descriptive analyses

The mean and standard deviation of the time participants spent on textual, visual, and multimedia tasks were calculated for both the deepfake benchmark test and the second round of manipulation testing.

Conceptual priming—textual tasks

In textual tasks, the average time spent detecting fake news (1st mean = 8.54, 2nd mean = 5.99) was shorter than the time spent detecting real news (1st mean=11.24, 2nd mean=7.44). However, variability was generally high (fake news 1st std = 17.4, 2nd std = 8.17, real news 1st std = 33.26, 2nd std = 15.66). This finding demonstrates that participants generally spend more time on text-based tasks and hold significantly differing opinions about them. Participants spent longer evaluating real articles due to the lack of obvious cues that indicate a higher cognitive load when relying only on semantic or contextual information.

Visual tasks

In visual tasks, the average detection times for fake photos (1st mean = 11.35, 2nd mean = 7.18) was longer than for real images (1st mean = 4.2, 2nd mean = 4.48) and showed high standard deviations (fake image 1st std = 36.28, 2nd std = 14.02). Participants spent less time on image detection than on textual tasks, even though their judgments of fake photos remained highly variable. Visual detection is faster but carries greater risk, as participants lack the linguistic context available in text and must rely on subtle perceptual cues that differ significantly between individuals.

Perceptual priming—multimedia tasks

Multimedia analysis showed the highest consistency across both rounds (fake video 1st std = 2.65, 2nd std = 2.21, real video 1st std = 2.88, 2nd std = 8.02). Moreover, the average time participants required to make judgments decreased significantly. The reduced time and variance indicate that multimedia priming generated stronger and more unified detection strategies because video provided multiple synchronised cues. They were able to form quick judgments in video tasks without extensive deliberation.

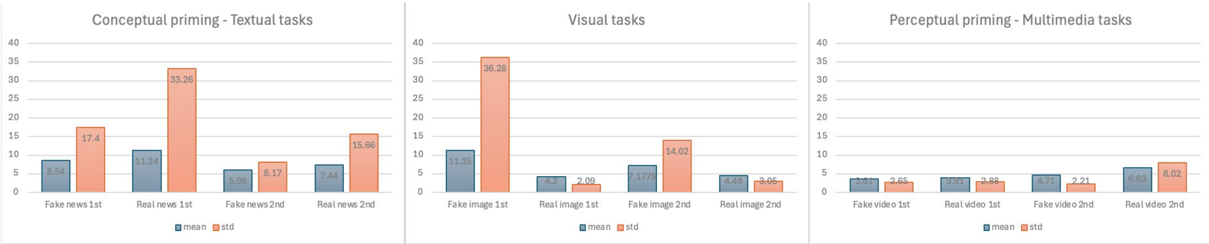

Figure 3. Baseline test (1st) and manipulated digital content test (2nd).

Qualitative analyses

A qualitative analysis of participants' responses identified key ideas that were refined into media types and priming effects.

Media types

According to media richness theory, multimedia content contains rich informational cues that can enhance clarity, reduce ambiguity, and require less time to make decisions. In contrast, lean media provide few cues, which increases detection difficulty and requires more cognitive processing time.

> P29 responded: '*Deepfakes in black-and-white are hard.*'

> P15 said, '*Short deepfake clips with no audio are hard.*'

Simplified media content limits cues for detecting manipulation, making deepfakes harder to identify and increasing cognitive effort. Thus, participants' difficulties arose from lack of judgmental clues.

Conceptual versus perceptual priming

Conceptual priming encouraged participants to adopt deliberate detection strategies for detecting deepfakes. Their reflections show how structured instructions shaped detection approaches.

> P6 noted, '*I remember the instruction about using fact-check tools.*'

> P7 stated, '*The instruction said to check uploader credibility.*'

This systematic approach supported participants in detection strategies adoption. When they recalled instructions for conceptual priming, they remembered the textual guidance that helped with identifying manipulation cues.

Perceptual priming enhanced sensitivity to anomalies, such as irregular movement or mismatched audio.

> P5 commented, '*I'd focus on deepfake-prone areas, treat subtle inconsistencies as red flags, and prioritise specialised verification to check for digital alterations.*'

Participants identified anomalies as key indicators in deepfake detection, with perceptual priming enhancing their ability to identify irregularities and improve accuracy.

Discussion

The findings demonstrate that media type shapes deepfake detection behavior. Participants invested greater cognitive effort when analysing lean media content because these formats provide fewer perceptual cues and require semantic reasoning. Longer reaction times and higher standard deviations in textual tasks indicate greater cognitive uncertainty and less consensus among participants. More importantly, the large standard deviations in deepfake tasks indicate substantial variability in individual strategies. This dispersion reveals that deepfake detection in low-information environments may depend heavily on idiosyncratic knowledge or prior experiences.

In contrast, although videos were perceived as the most challenging, judgments in video tasks were faster and more consistent. This finding aligns with media richness theory, which explain information rich channels reduce ambiguity by enabling simultaneous cue processing. In such cases, perceptual heuristics can outperform analytical reasoning. The results show that videos are an information rich media; the more information they contain, the more clues they provide. People can often spot deepfakes simply by noticing subtle inconsistencies.

The results also clarify how the two priming types influence distinct cognitive pathway. Conceptual priming activated reflective, rule-based strategies. Participants explicitly recalled deepfake detection instructions, source verification rules, and evaluation methods. These behaviors align with analytical reasoning (system 2) and compensate for missing cues in lean media. Perceptual priming improved sensitivity to anomalies, particularly in video analysis. Participants' insights all came from perceptual anomalies linked to perceptual priming. With guidance, participants' intuitive judgments (system 1) improved their deepfake detection rates. These complementary findings suggest priming effectiveness depends on media richness. When media are lean, conceptual strategies reduce cognitive uncertainty. When media are rich, perceptual strategies activate rapid anomaly detection.

Implications and limitations

Our study demonstrates that deepfake evaluation is not a uniform cognitive task. Instead, priming effects can enhance deepfake detection, with perceptual priming being more effective than conceptual priming in multimedia. Rich media expose more cues for anomalies within deepfake content, supporting media richness theory. Dual process theory also explains how perceptual cues enable individuals to make rapid judgments using the intuitive system. However, limited cues in lean media trigger deeper analysis through the reflective system. These findings suggest that individuals' strategies for evaluating deepfakes can be interpreted in information diversity and cognitive load.

As a pilot study, the small sample size limits the generalisability of the findings, and the study relied on reaction time and self-report measures. Future research will incorporate physiological indicators or standardised digital literacy assessments to strengthen objective validation. Nonetheless, this study establishes a foundation for integrating media richness and dual process theories into an information priming framework. It contributes to the advancement of effective deepfake detection strategies by offering a cognitive approach that incorporates human factors. Importantly, participants were better at detecting manipulations in rich media than in lean media, suggesting that video deepfakes may not always be the hardest to detect.

Future study and conclusion

Future research should expand participant recruitment and explore how conceptual and perceptual priming interact with dual process mechanisms across different media platforms. Additional research could also investigate other factors and interventions aimed at strengthening reflective processing and reducing overconfidence.

As deepfake technology advances, enhancing human cognitive resilience is just as important as developing technical defenses. Although deepfake content has a profound impact on society, this challenge is not impossible to address. People can detect manipulated elements through multimedia cues, raising concern and prompting further investigation.

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