The 2024-2025 Fluency Report: Bridging the AI Digital Divide

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Our Approach

Research Focus

Our objective was to explore the intersection of artificial intelligence (AI), journalism, and the digital divide. This approach centers on the concept of the AI digital divide, examining the access, usage, and assessment of AI-generated content. By grounding the investigation in both media and technology studies, the research connects the increased production of synthetic media with systemic gaps in digital literacy and infrastructure. Our inquiry is also guided by a human-centered lens, utilizing accepted journalistic norms and standards to provide a second layer of analysis.

Definition of AI Digital Divide

The AI digital divide refers to the growing gap between individuals and organizations that can effectively use, understand, and benefit from AI technologies and those that cannot. Unlike earlier digital divides focused solely on access to hardware or internet, the AI divide encompasses varying access in digital literacy, skill acquisition, and the ability to interpret or question AI-generated outputs. It highlights issues of transparency, accountability, and the distribution of resources, training, and support. This divide has consequences for industries such as journalism and education, as AI systems increasingly support how we receive and interpret information.

AI Digital Divide: Important Factors

Several factors drive the widening AI digital divide. These include educational access, geography, and institutional investment in AI development and training.

- **Structural level:** At the structural level, high concentrations of AI innovation and patents are found in a small number of countries and corporations, leaving other regions under-resourced.
- **Individual level:** At the individual level, access to training and upskilling defines each person's benefit from AI technologies.
- **Transparency:** Many AI systems operate in ways that are opaque to both experts and the general public. Without clear explanations of how decisions are made or content is generated, it becomes difficult for users to assess credibility or understand the limitations and biases of AI systems.
- **The Black Box:** AI systems, especially those based on deep learning, produce outputs through complex internal processes that are not easily interpretable. Bridging the divide means making these systems more transparent, explainable, and accessible to all.

AI Digital Divide Factors

Under-resourced Regions with Transparent AI

Under-resourced regions benefit from transparent AI despite limited access.

Transparent AI Systems
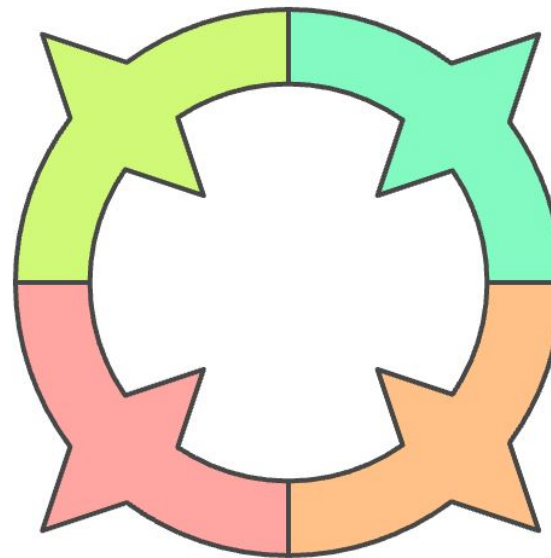
Transparent AI systems enhance user understanding and trust.

Opaque AI Systems in Under-resourced Regions

Opaque AI systems exacerbate challenges in under-resourced regions.

High-Access but Opaque AI Systems

High-access but opaque AI systems lack user understanding.

High Transparency

Low Access

High Access

Low Transparency

Made with Napkin

How to Bridge the Divide

Summary

Our research examined how AI detection tools can identify and attribute AI-generated media grounded in the aforementioned discussion of AI access and effectiveness.

Research Summary

- With proper training, AI analytics can identify and trace the origins of manipulated or synthetic media content.
- Empirical studies show image-based analytics outperform text-based methods in detecting synthetic media, revealing the need for improved text analysis tools.
- Limitations persist due to AI's rapid evolution and the black box phenomenon - factors that can widen the AI divide unless addressed in future research.

Methodology

This research combined critical analysis of scholarly literature with two studies of AI-generated detection efforts. Drawing on academic, industry, and policy sources, we examined how detection tools work and how accessible or usable they are in context of the AI divide. Particular attention is paid to the role of GANs, diffusion models, and algorithms used for both generation and detection, alongside how access factors influence the adoption and effectiveness of these tools.

Example of an Inconsistent Image

Intramodal inconsistency - when discrepancies appear within a single media modality - is exemplified in this image, where the woman's mismatched earrings (highlighted by red arrows and inset photos) illustrate a common flaw found in AI-generated content (AIGC).
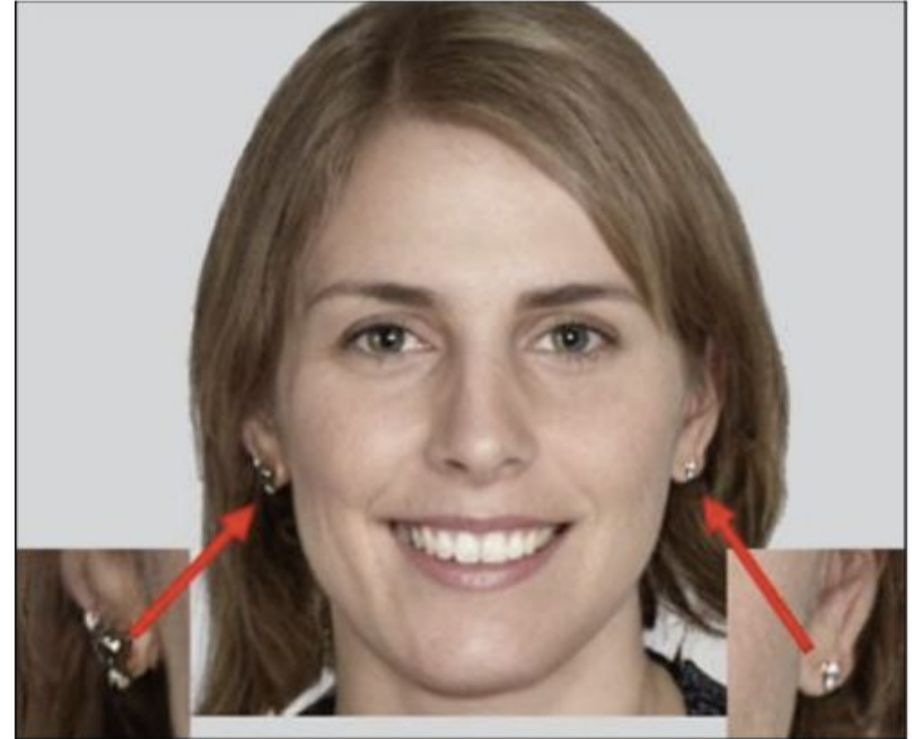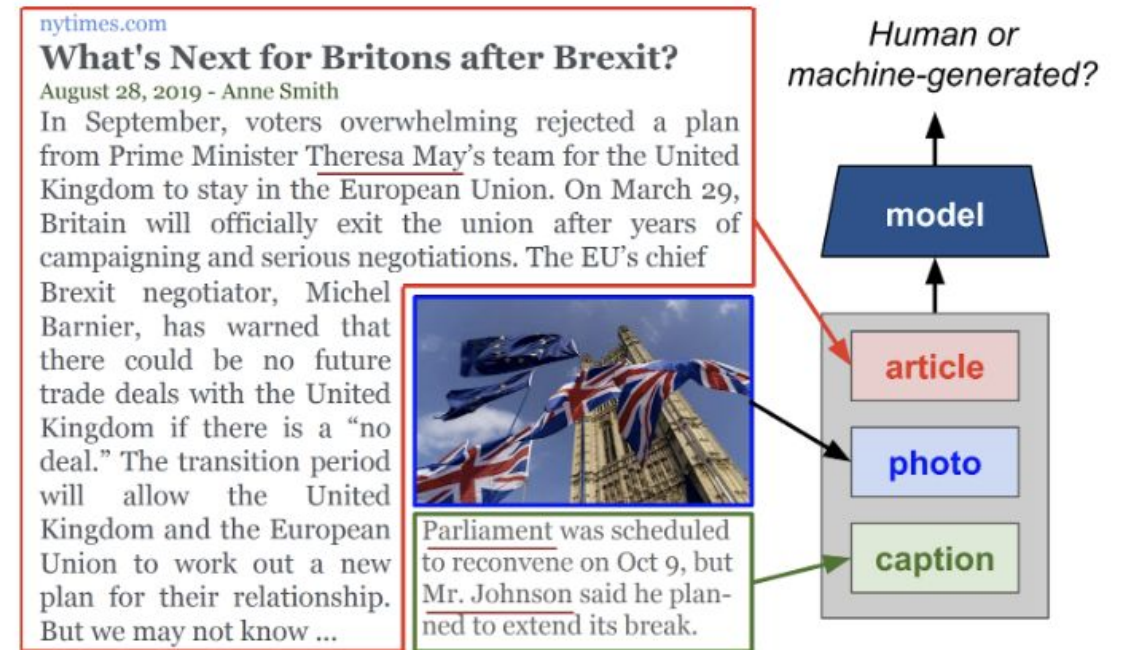

Image Inconsistency

Defense Advanced Research Projects Agency. (2019, September 3). *Uncovering the who, why, and how behind manipulated media*. DARPA. https://www.darpa.mil/news/2019/uncovering-manipulated-media

Example of an Inconsistent Multimodal Asset

The asset here shows two modalities - text in the caption and article, along with a photo - demonstrating how the trained AI detection analytics must process both text and imagery, or even text and video. This allows the tool to make broader judgments through comparative analysis of multiple media forms, with multimodal detection often focusing on news article captions and images (similar to social media content).

Multimodal Inconsistency

Reuben Tan, Bryan Plummer, Kate Saenko. 2020. "Detecting Cross-Modal Inconsistency to Defend Against Neural Fake News." Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), https://doi.org/10.18653/v1/2020.emnlp-main.163 https://hdl.handle.net/2144/42931

Addressing the Impact of the AI Divide

Results

Our results include the following insights:

- While AI detection tools are becoming more accurate in identifying synthetic content, attribution remains a challenge, as many AI-generated assets lack clear origin tracking.
- Training AI systems for attribution and promoting equitable access to detection tools are emerging as vital strategies in mitigating the harms of AI-generated misinformation.
- AI analytics are more effective at detecting image-based manipulation than text-based falsification, highlighting a gap in current detection capabilities.
- Theoretical frameworks that include human-led analysis improve AI's ability to detect and attribute synthetic or misattributed media in journalistic contexts.
- AI detection tools can successfully distinguish between genuine and manipulated author/organization attributions by leveraging multimodal and contextual features.

Future Implications

Looking forward, addressing the AI digital divide requires a concerted effort to invest in digital and AI literacy, ensuring that individuals can fully engage with AI technologies. This investment is crucial for equipping people with the skills necessary to understand and navigate the evolving digital landscape. Furthermore, establishing transparent AI models will allow users increased access and understanding, particularly in sectors like journalism and education.

In journalism, advanced AI detection technologies can aid in verifying content and attributing sources accurately. Similarly, in education, AI tools can be harnessed to provide personalized learning experiences, with transparency and literacy key to its success there. By prioritizing AI literacy, industries can help bridge the digital divide and transform how we engage with and harness this powerful tool in both our professional and personal lives.

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