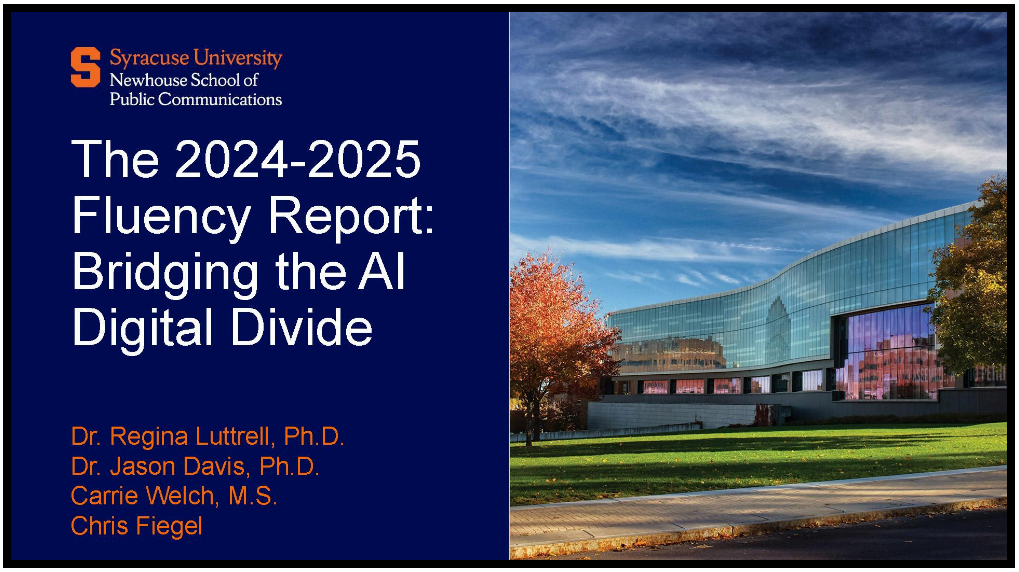
Slide 1: The 2024-2025 Fluency Report: Bridging the AI Digital Divide



Slide 1: The 2025 Fluency Report: Bridging the AI Digital Divide

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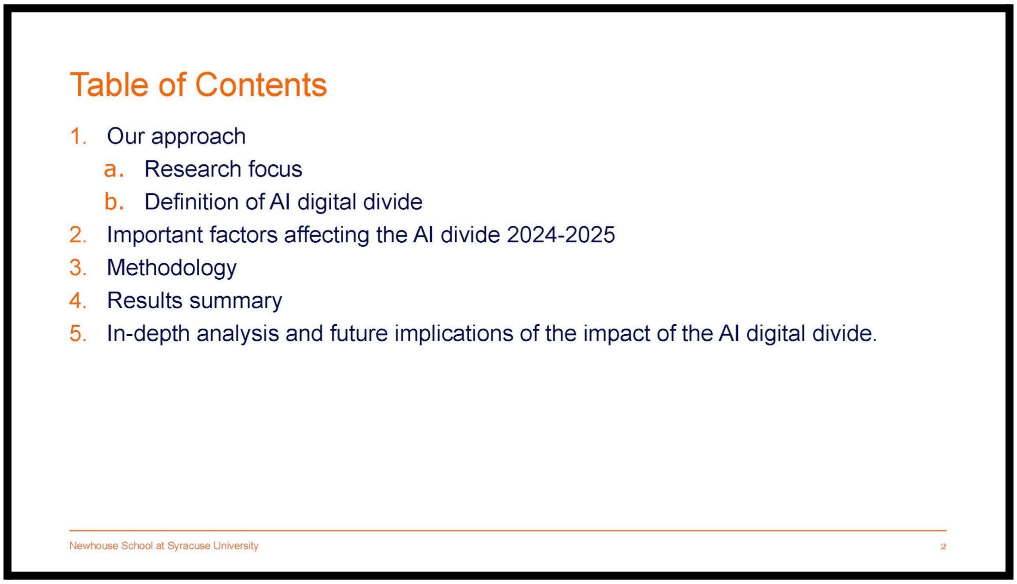
Dr. Jason Davis, Ph.D.
Carrie Welch, M.S.
Chris Fiegel

Photo of the S.I. Newhouse School Of Public Communications at Syracuse University.

Slide 2: Table of Contents



Slide 2: Table of Contents

1. Our approach
    a. Research focus
    b. Definition of AI digital divide
2. Important factors affecting the AI divide 2024-2025
3. Methodology
4. Results summary
5. In-depth analysis and future implications of the impact of the AI digital divide.

Slide 3: Our Approach

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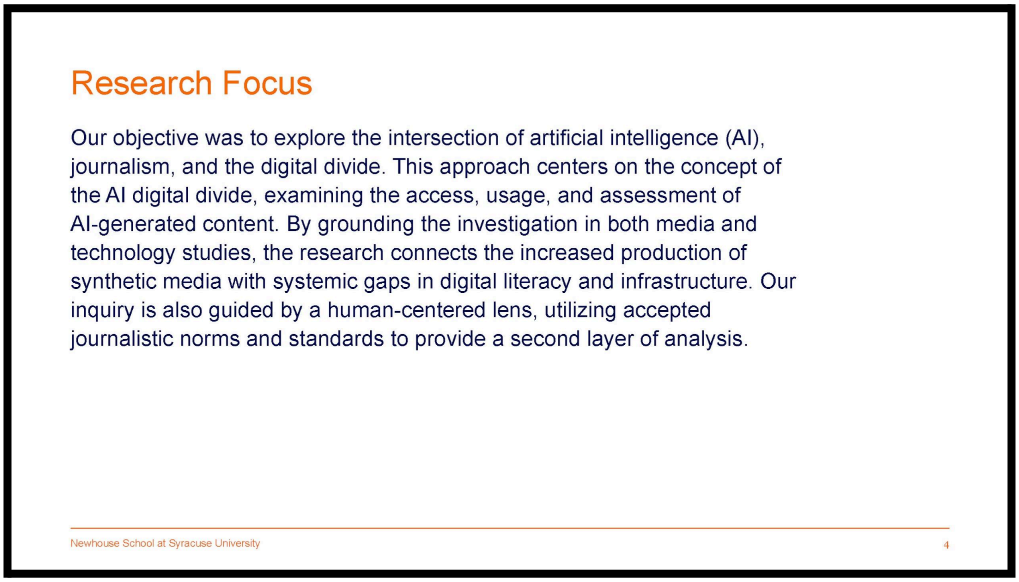
Photo of a large group of people outside S.I. Newhouse School Of Public Communications at Syracuse University.

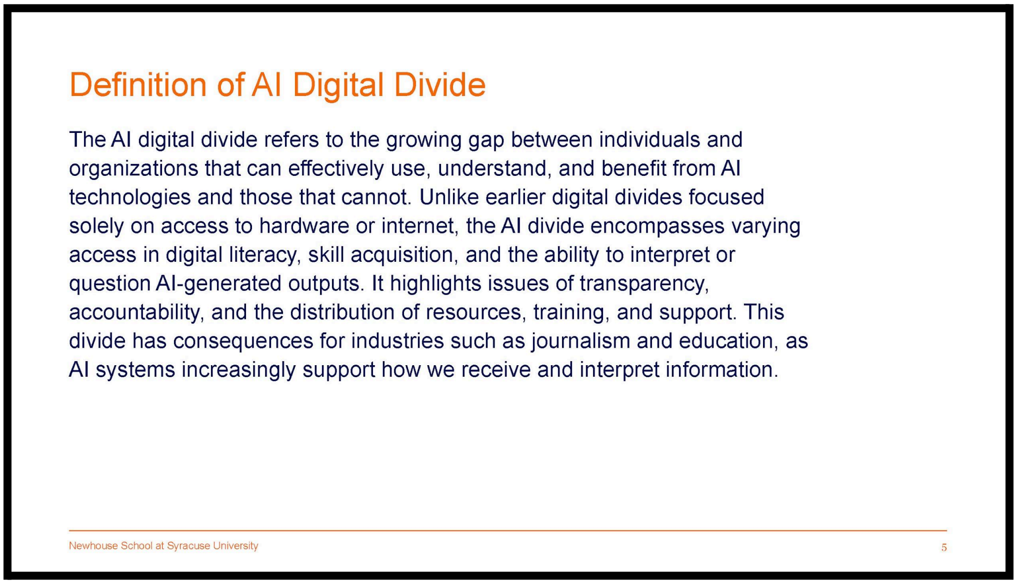
Slide 4: Research Focus



Slide 4: 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.

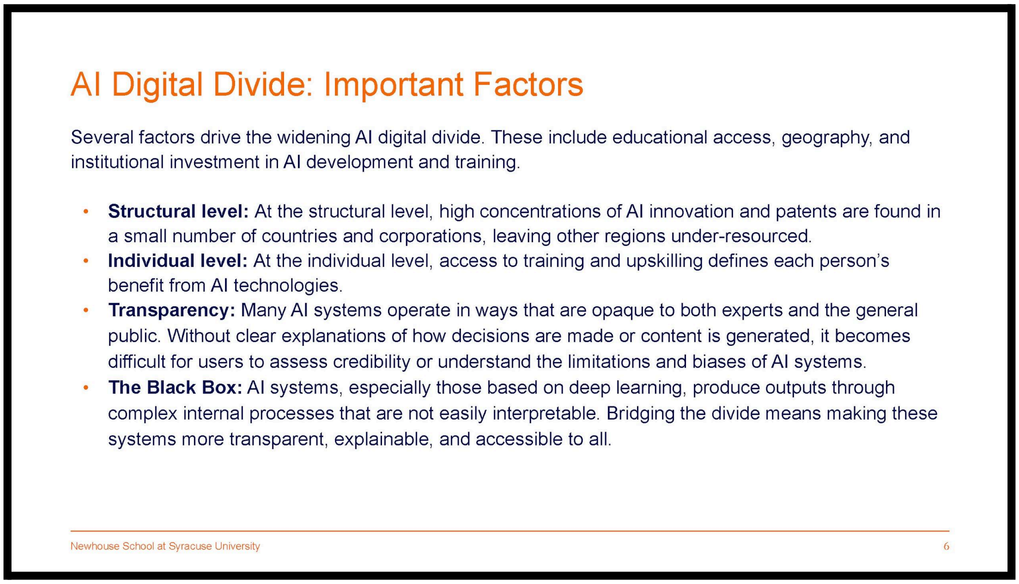
Slide 5: Definition of AI Digital Divide



Slide 5: 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.

Slide 6: AI Digital Divide: Important Factors



Slide 6: 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.

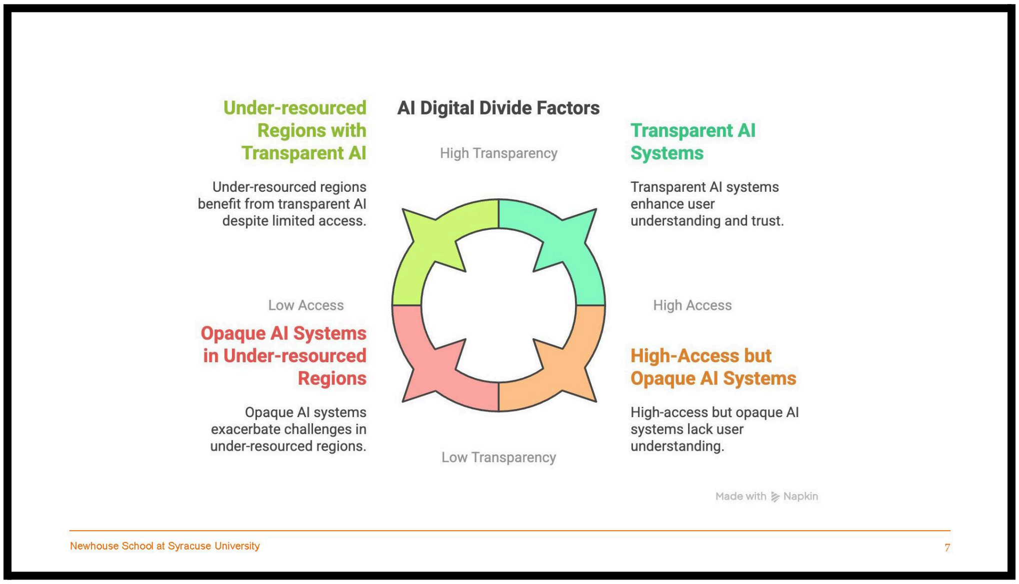
Structural level: At the structural level, high concentrations of AI innovation and patents are found in a small number of countries and corporations, leaving other regions under-resourced.

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.

Slide 7: AI Digital Divide Factors



Slide 7: Experimental-design survey: Measures

- High Transparency, Low Access
  - Under-resourced Regions with Transparent AI
    - Under-resourced regions benefit from transparent AI despite limited access.
- High Transparency, High Access
  - Transparent AI Systems
    - Transparent AI systems enhance user understanding and trust
- Low Transparency, High Access
  - High-Access but Opaque AI Systems
    - High-access but opaque AI systems lack user understanding.
- Low Transparency, Low Access
  - Opaque AI Systems in Under-resourced Regions
    - Opaque AI systems exacerbate challenges in under-resourced regions.

Circular diagram titled “AI Digital Divide Factors” showing four quadrants that represent different AI system scenarios. The top-left quadrant (green-yellow) represents high transparency but low access systems. The top-right quadrant (mint green) shows both high transparency and high access systems. The bottom-right quadrant (orange) represents low transparency but high access systems. The bottom-left quadrant (pink) shows both low transparency and low access. Arrows connect the quadrants in a circular flow. The diagram was created with the online tool Napkin AI.

Slide 8: How to Bridge the Divide

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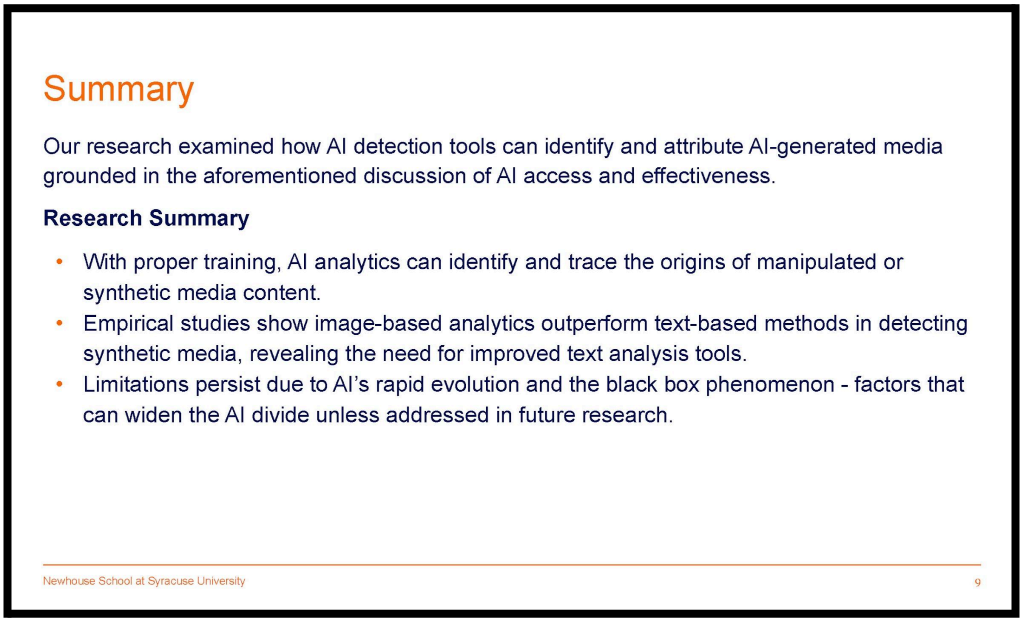
Photo of a large group of people outside S.I. Newhouse School Of Public Communications at Syracuse University.

Slide 9: Summary



Slide 9: 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.

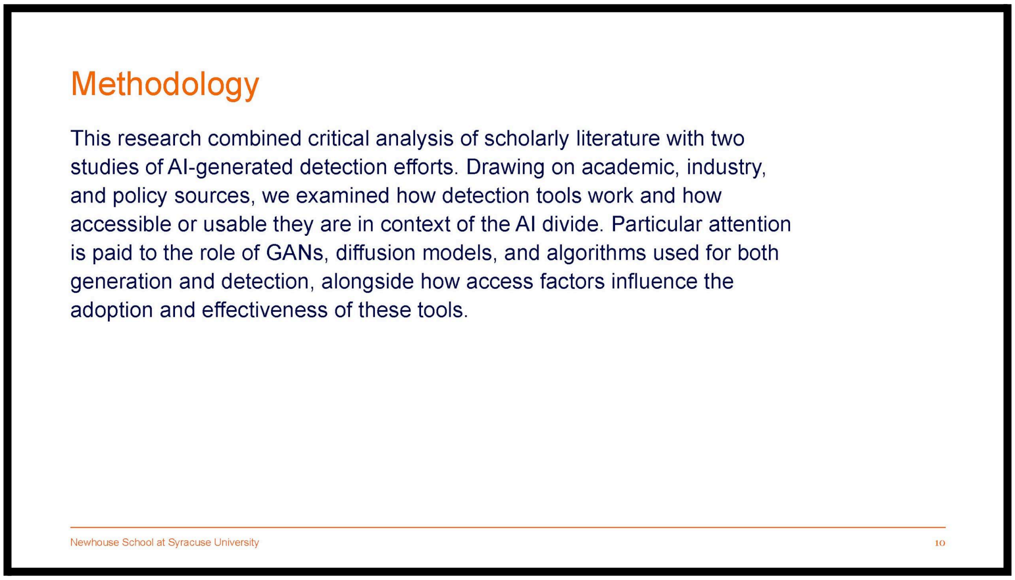
Research Summary

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.

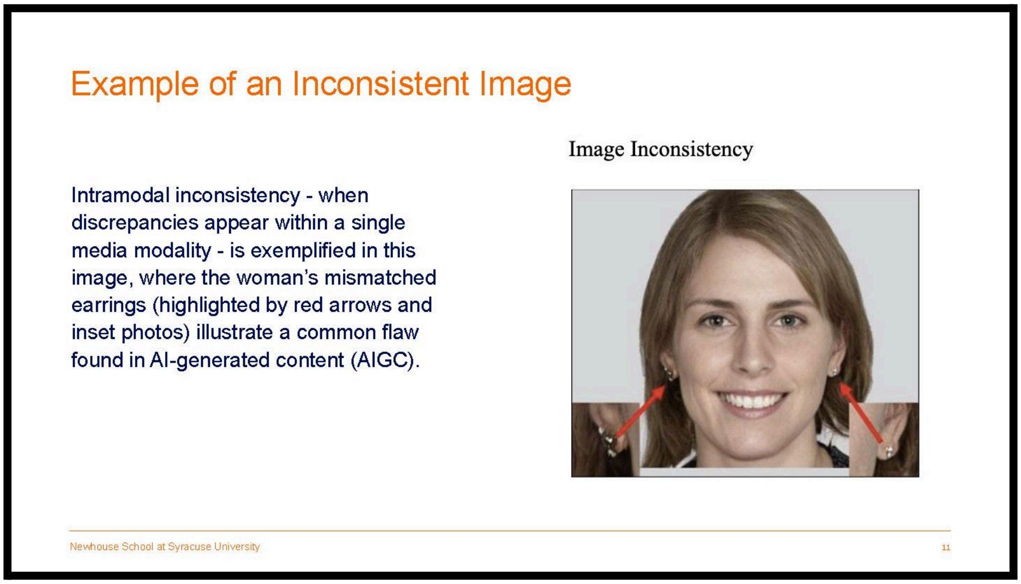
Slide 10: Methodology



Slide 10: 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.

Slide 11: Example of an Inconsistent Image

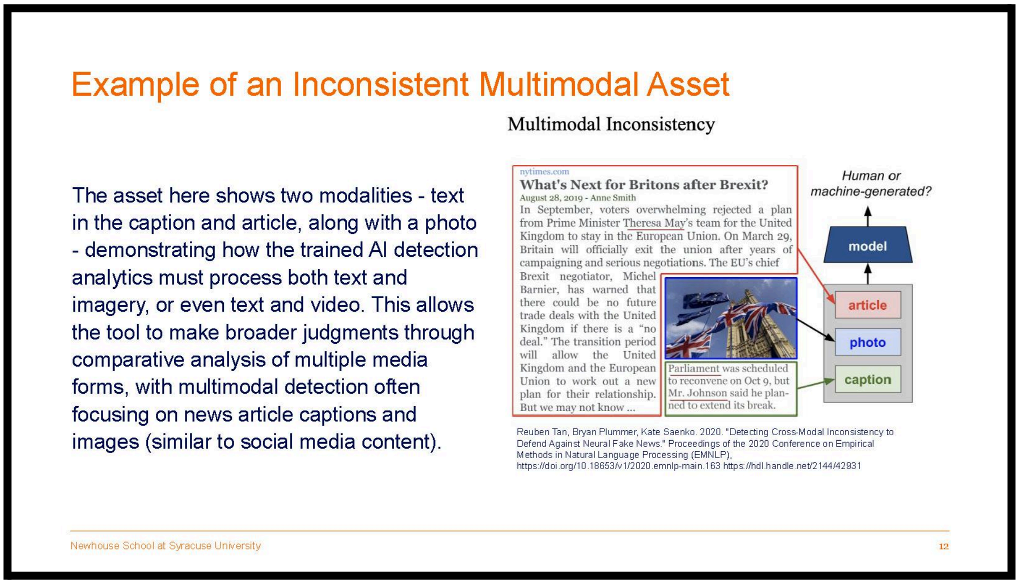


Slide 11: Example of an Inconsistent Image

> 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).

A diagram titled "Image Inconsistency" showing a manipulated portrait photo with red arrows pointing to areas where image inconsistencies are visible; the photo shows a AI-generated woman with shoulder-length hair and a smiling expression.

Slide 12: Example of an Inconsistent Multimodal Asset



Slide 12: 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).

A diagram titled “Multimodal Inconsistency” showing analysis of a news article about Brexit, written by Anne Smith on August 28, 2019. The diagram includes labeled sections of text, photo, and caption, with annotations indicating how to determine if content is human or machine-generated. The article headline reads “What's Next for Britons after Brexit?”

The reference for the diagram is listed:

> 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

Slide 13: Addressing the Impact of the AI Divide

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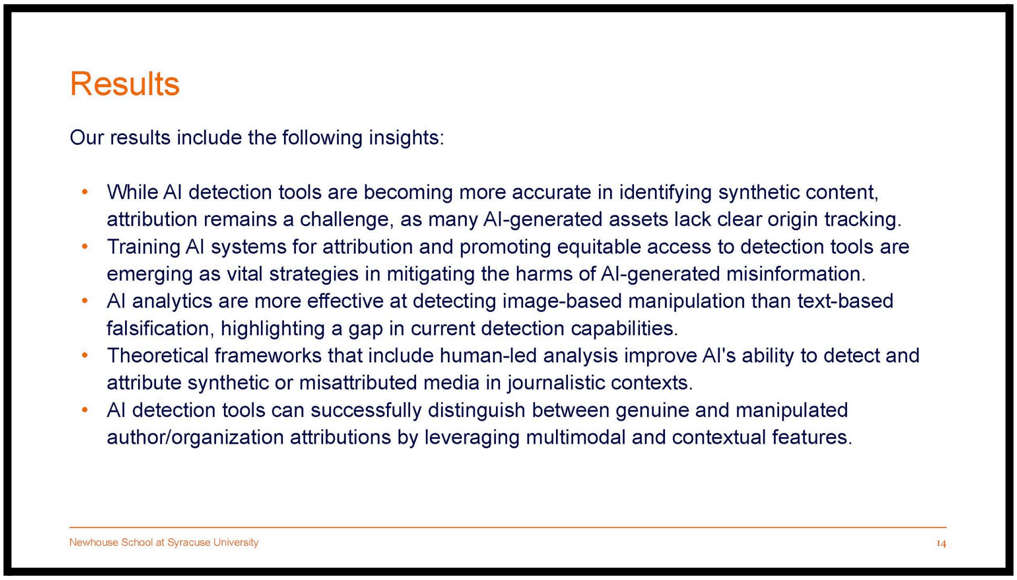
Photo of a large group of people outside S.I. Newhouse School Of Public Communications at Syracuse University.

Slide 14: Results



Slide 14: 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.

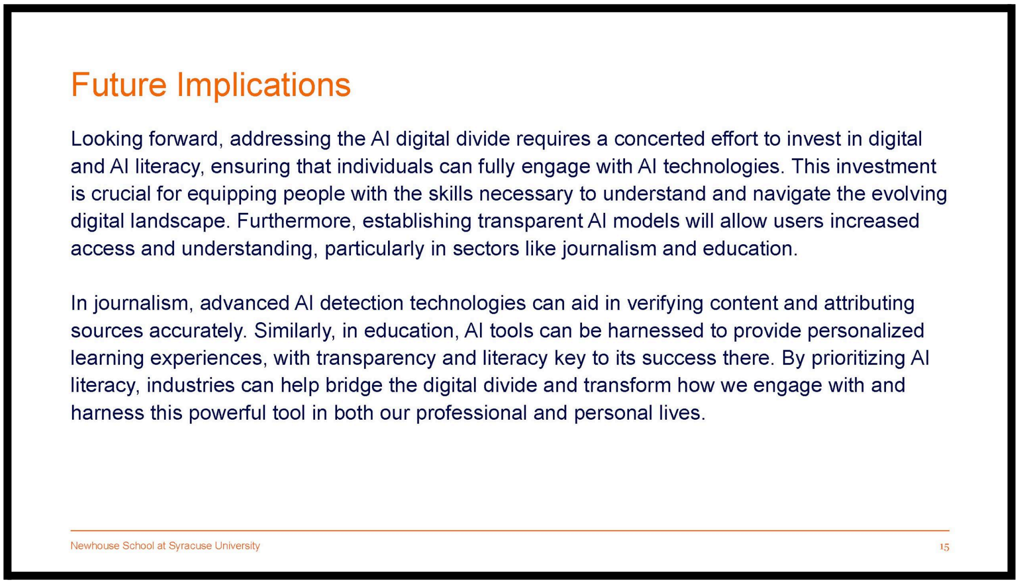
Training AI systems for attribution and promoting equitable access to detection tools are emerging as vital strategies in mitigating the harms of AI-generated misinformation.

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.

Slide 15: Future Implications



Slide 15: 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.

Slide 16: Works Cited

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