



Oregon State
University

Generative AI in Journalism Report

AUTHORS

Shrirang Patil - 934534470
Gowtham Arulmozhi - 934538589
Jibin Yesudas Varghese - 934552920

January 21, 2025

Contents

1	Executive Summary	1
	Executive Summary	1
2	Identifying and Explaining the Social Context & Its Problem	1
2.1	Decline of Local News Outlets: A Deepening Crisis	2
2.2	Media Manipulation and Disinformation: A Sociotechnical Perspective	5
2.3	Economic Pressures on Journalism: Navigating the Digital Disruption	7
2.4	The Potential Role of Large Language Models in Journalism	10
3	Technical De-mystification	12
3.1	Background	12
3.2	Overview of Generative AI	13
3.3	Towards Journalism	13
3.4	Limitations and Challenges	14
4	History of the Technology	15
4.1	Early Beginnings and Statistical Models	15
4.2	From LSTM to Transformers: The Evolutionary Path to Large Language Models .	15
4.3	Emergence of Generative AI in Big Tech: A Paradigm Shift	16
4.4	Derivative Datasets and Specific Applications	17
4.5	Generative AI in Journalism	18
5	Privacy Analysis	20
5.1	Theoretical Framework of Consent	20
5.2	Understanding Compensation in Generative AI in Journalism	22
5.2.1	Case Study:OpenAI vs New York Times	23
5.2.2	Case Study: The Intercept, Raw Story, and AlterNet vs. OpenAI and Mi- crosoft	24
5.3	Implications of Using Public Data Without Explicit Consent	25
6	Power & Justice Analysis	26
6.1	Systems of Classification and Ethical Considerations	26
6.2	Shifting Power Dynamics	28
6.3	Algorithmic Bias and Disparate Impact	29
6.4	Sociotechnical Systems and Power Shifts	30
7	Accountability Analysis	31

7.1	Principles of Accountability of Generative AI in Journalism	31
7.1.1	Transparency and Explainability	31
7.1.2	Responsibility and Fairness	32
7.2	Analyzing Accountability in AI-Driven Journalism	34
7.2.1	Accountability Gaps and Moral Crumple Zones	34
7.2.2	Consultation and Involvement of Impacted Individuals	35
7.2.3	Resources for Stakeholder Engagement	36
8	Generative AI: A Double-Edged Sword for Publishers	37
9	Normatively Informed Recommendations	37
9.1	Recommendations for News Organizations in the AI Era	38
9.1.1	Implement Robust Ethical Guidelines	38
9.1.2	Invest in AI Training for Journalists	38
9.1.3	Promote Transparency in AI Usage	38
9.2	Journalists Embrace AI as a Tool for Enhancing Journalism	39
9.3	Establishing Regulatory Frameworks by Policy Makers	39
	List of Figures	I
	References	II

1 Executive Summary

The integration of generative AI into journalism is a multifaceted development that presents both opportunities and challenges. The "Generative AI in Journalism Report", provides a comprehensive analysis of these dynamics. The report highlights the decline of local news outlets, the rise of media manipulation and disinformation, and the economic pressures reshaping journalism as critical issues that generative AI could potentially address.

The decline of local news outlets has created "news deserts," particularly in rural and economically disadvantaged areas, leading to increased political polarization, reduced accountability, and the spread of misinformation. Generative AI offers a potential solution by automating routine reporting tasks, thereby freeing journalists to focus on in-depth investigations and nuanced storytelling. This could help fill the void left by the decline of local news and provide communities with access to relevant news and information.

However, the report also underscores significant challenges associated with the use of generative AI in journalism. These include the potential for generating misinformation, the risk of algorithmic bias, and the economic impact on the journalism industry, including job displacement for journalists. The ethical implications of using public data without explicit consent and the need for robust accountability mechanisms are also critical concerns.

To address these challenges, the report recommends implementing robust ethical guidelines, investing in AI training for journalists, and promoting transparency in AI usage. It also emphasizes the importance of establishing regulatory frameworks to ensure the ethical and responsible use of AI in journalism. By fostering collaboration between AI developers, news organizations, and policymakers, the report suggests that it is possible to harness the capabilities of generative AI while mitigating its risks, thereby supporting a resilient and dynamic journalistic landscape. While generative AI holds significant promise for enhancing journalism, it is essential to navigate its integration carefully to ensure it contributes positively to public discourse and upholds the integrity of journalism.

2 Identifying and Explaining the Social Context & Its Problem

The field of journalism is integrating Large Language Models (LLMs) into a quickly changing and intricate social setting. Numerous crucial challenges, such as the demise of local news sources, the spread of misinformation and media manipulation, and the financial strains on traditional journalism, define this setting. When LLMs are introduced, a social environment that is both susceptible to and capable of transformation is created by these elements taken together.

2.1 Decline of Local News Outlets: A Deepening Crisis

The collapse of local news outlets in the United States poses a significant threat to the fabric of democracy and community cohesion. This phenomena, typified by newspaper closures and a reduction in local media resources, has far-reaching repercussions for public involvement, accountability, and the dissemination of misinformation. This section digs into the multifaceted dilemma of disappearing local news, using recent research and publications to shed light on the extent, causes, and repercussions of this alarming trend.

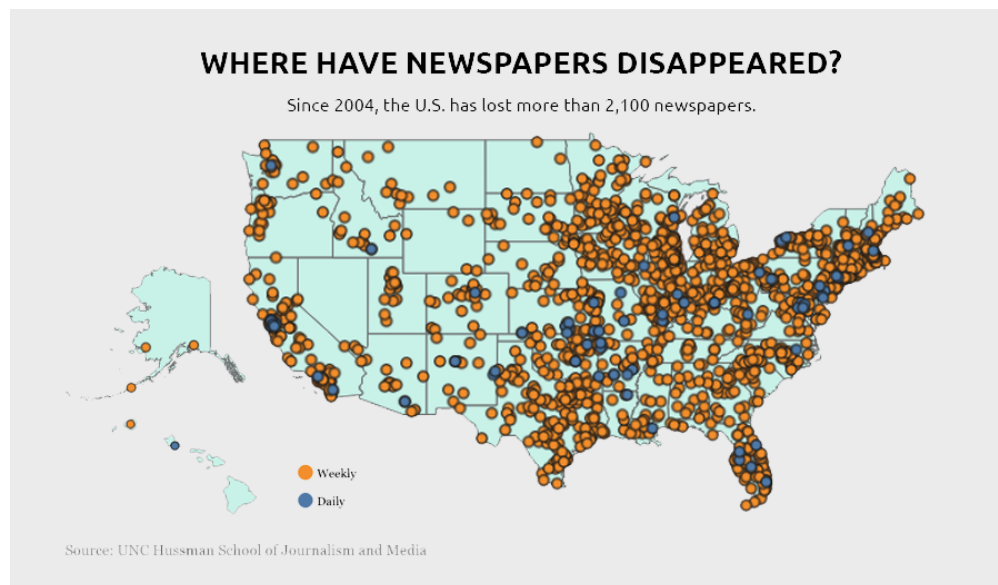


Figure 1: A map that displays communities where newspapers have disappeared (UNC Hussman School of Journalism and Media)

The number of local news outlets in the United States has decreased dramatically since the turn of the century. According to a Northwestern University research, the country has lost roughly 2,900 newspapers since 2005, accounting for one-quarter of the total number, indicating a dramatic shrinkage in the local journalism scene [1]. This reduction is not only numerical; it signifies a significant degradation of journalists' ability to cover local events comprehensively. According to the Medill School of Journalism at Northwestern University, newsroom staffing has dropped by 60% during the same time period, worsening the crisis by diminishing the depth and breadth of local news coverage[2].



Figure 2: News Desert Illustration by Adria Fruitos

The shutdown of local newspapers has resulted in the establishment of "news deserts," locations where residents have little access to local news and information[3][2]. These deserts are especially frequent in rural and economically disadvantaged communities, leaving large segments of the population without access to information about local governance, community events, and public issues. A news desert, according to the University of North Carolina's Center for Innovation & Sustainability in Local Media, is a community with limited access to authentic and comprehensive news and information that serves as a grassroots source of democracy[3]. This definition emphasizes the importance of local news in promoting democratic engagement and accountability.

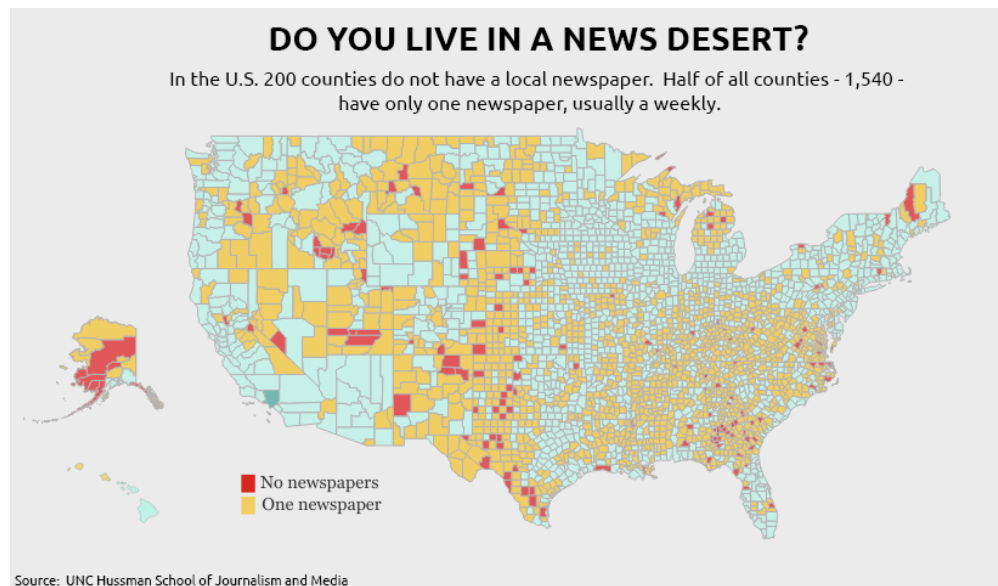


Figure 3: A map that displays News Deserts (UNC Hussman School of Journalism and Media)

The failure of local news outlets has various far-reaching effects for American society and democracy, including (i) increased political polarization, Studies have found that a lack of local news corresponds with higher political polarization. Without local news to give balanced and community-specific coverage, locals turn to national news sources, which frequently highlight party conflict[4]. This trend contributes to a more polarized public, which is less capable of engaging in informed and respectful debate. (ii) Increased corruption and decreased accountability. The watchdog role of the local press is critical in exposing wrongdoing and holding public authorities responsible. With fewer journalists investigating local governments and corporations, examples of corruption, waste, and misconduct are less likely to be exposed[5][6]. This lack of oversight emboldens unethical behavior and undermines public trust in institutions. (iii) The spread of misinformation The void created by the decline of local news channels is frequently filled by less reliable sources, such as social media platforms where disinformation can proliferate unchecked [7][5]. The lack of credible local news sources leaves communities more vulnerable to disinformation, which has serious consequences for public health, safety, and confidence.

Philanthropic backing, the formation of nonprofit news models, and measures to improve public digital literacy have all been used to counteract the decline in local news [8][9][10]. These initiatives seek to build long-term models for local journalism that can resist the economic challenges that have triggered the current crisis. Furthermore, there is a rising acknowledgment of the necessity for public policy solutions to sustain the local news ecosystem, which recognizes its critical role in democracy[9][10].

2.2 Media Manipulation and Disinformation: A Sociotechnical Perspective

Media manipulation and disinformation pose serious dangers to the stability of democratic nations. The internet's participatory culture, which was once lauded for democratizing information dissemination, has been co-opted by a variety of players to manipulate public opinion and undermine institutions. This manipulation is not a result of digital contact, but rather an intentional exploitation of the sociotechnical mechanisms that support current communication networks. Troll armies, doxxing, algorithm gaming, and the strategic dissemination of false information are some of the strategies used to influence public debate and undermine trust in media and governance[11].



Figure 4: Trolling and Media Manipulation Image by Luis Assardo

Tactics of media manipulation include (i) troll armies and doxxing. Organized groups of internet trolls launch orchestrated attacks to harass people, overwhelm social media with harmful content, and disrupt debates. Doxxing, the practice of revealing private or identifiable information about people without their knowledge, is frequently used to intimidate or penalize those who have

opposing views. These methods add to a hostile online environment by deterring participation in open conversations and chilling free expression[12][11]. (ii) Algorithmic gaming. Manipulators frequently exploit algorithms that determine what content is displayed on social media networks. Bad actors can manipulate algorithms to make some content appear more popular or reputable than it is. This can distort public perception and produce misleading narratives that gain traction only because they appear in people's feeds[12][13]. (iii) The spread of false information. The propagation of false or misleading information is a defining feature of media manipulation. This is frequently accomplished through the creation of sensationalist, emotionally charged content intended to go viral. Such content generally exploits existing societal divisions, intensifying disputes and weakening a shared concept of reality[12].

The sociotechnical structure of today's media ecosystems contributes significantly to the efficacy of media manipulation methods. These ecosystems are complex networks in which social behaviors and technology infrastructures interact in potentially exploitable ways. For example, the architecture of social media platforms that promote engagement (e.g., likes, shares) may unintentionally favor sensational material, regardless of its veracity. This design, combined with human cognitive weaknesses such as confirmation bias and the echo chamber effect, provides a ripe environment for disinformation to thrive[11]. Furthermore, the internet's worldwide reach and anonymity allow disinformation to spread quickly across national borders, making it a transnational concern. The actors engaging in these campaigns vary from state-sponsored groups to unaffiliated political fanatics, each with their own objective[11].

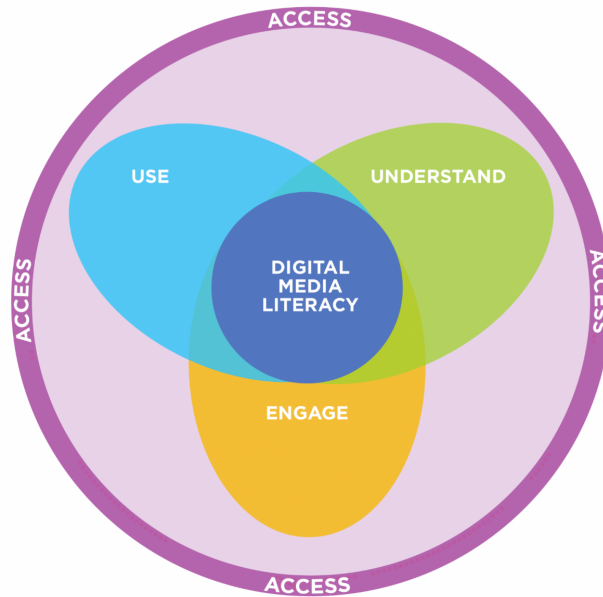


Figure 5: Digital Media Literacy

Addressing the issues raised by media manipulation necessitates a diverse strategy. First, there is a need for increased media literacy in the general population to assist people notice and critically analyze the content they receive online[14]. Second, technology companies must continue to fine-tune their algorithms to penalize deceptive content and increase the openness of content moderation processes[13]. Furthermore, policymakers and civil society organizations should work together to develop norms and legislation that prevent media manipulation while protecting free speech. Given the transnational character of digital media and the global reach of disinformation efforts, international cooperation will be critical[11].

2.3 Economic Pressures on Journalism: Navigating the Digital Disruption

The internet and digital platforms have transformed the media landscape, putting unprecedented economic pressure on the journalism business. The internet has profoundly changed how news is consumed, resulting in a major reduction in traditional revenue streams for journalism. The transition from print to digital has altered not only consumption habits, but also advertising revenue methods. As digital platforms became the major medium for news consumption, traditional newspapers and magazines experienced a significant drop in print sales and advertising revenue[15][16]. This trend has been worsened by the dominance of tech behemoths like Google and Facebook in the digital advertising sector, which have captured a sizable portion of the advertising money that

traditionally funded journalism[15][17].

Table 1.

Decline of U.S. Physical Media by Estimated Revenue for Employer Firms: 2002-2020

(In millions of dollars)

NAICS industry ¹	2002	2010	2020
Newspaper Publishers	46,179	33,360	22,149
Periodical Publishing	40,181	31,876	23,919
Directory and Mailing List Publishing	16,920	11,987	4,409
Video Tape and Disc Rental	9,364	6,056	1,077

¹ North American Industry Classification System (NAICS).

Note: Data not adjusted for price changes. Differences in revenue estimates may be attributed to sampling or nonsampling error, rather than underlying economic conditions. Caution should be used in drawing conclusions from the estimates and comparisons shown. Additional information on survey methodology, including sampling and nonsampling error, sample design, and confidentiality protection can be found at <www.census.gov/programs-surveys/sas/technical-documentation/methodology.html>. The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied (Approval ID: CBDRB-FY21-256).

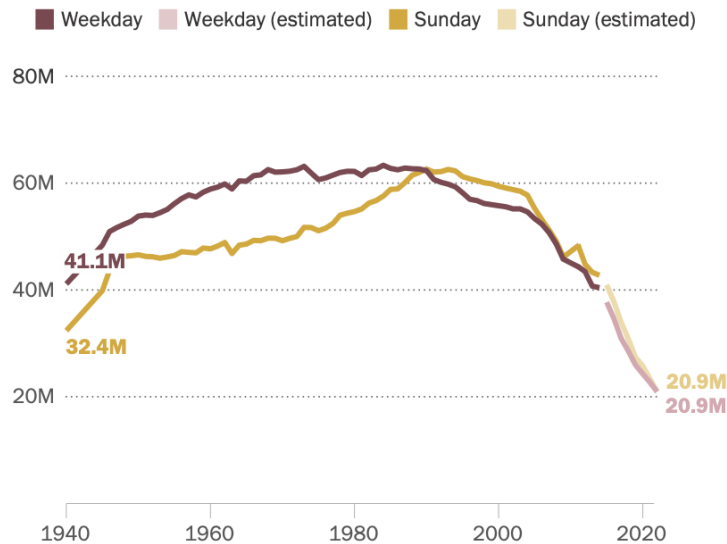
Source: U.S. Census Bureau, 2020 Service Annual Survey and Service Annual Survey Historical Tables.

Figure 6: Table of the financial hit industries took between 2002 and 2020

Another aspect of economic pressures on journalists is the phenomena of news fatigue. The relentless flood of news, particularly during major global catastrophes like the COVID-19 epidemic, has resulted in a rising segment of the population purposefully ignoring it[18]. This trend of news avoidance directly threatens the economic viability of news organizations, since decreased engagement leads to lower advertising revenues and fewer subscriptions[18][19].

U.S. daily newspaper circulation continues to decline

Total circulation of U.S. daily newspapers



Note: To determine totals for 2015 onward, researchers analyzed the year-over-year change in total weekday and Sunday circulation using AAM data and applied these percent changes to the previous year's total. Only those daily U.S. newspapers that report to AAM are included. Affiliated publications are not included in the analysis. Weekday circulation only includes those publications reporting a Monday-Friday average. Comparisons are either between the three-month averages for the period ending Dec. 31 of the given year and the same period of the previous year (2015-2019), the six-month period ending Sept. 30 and the three-month period ending Sept. 30 of the previous year (2020), or the six-month period ending Sept. 30 of the given year and the same period of the previous year (2021-2022). Source: Editor & Publisher (through 2014); estimate based on Pew Research Center analysis of Alliance for Audited Media data (2015-2022).

PEW RESEARCH CENTER

Figure 7: U.S. daily newspaper circulation continues to decline

The economic issues facing the media business have had a significant impact on newsroom operations. Many news organizations have been compelled to implement cost-cutting measures, such as layoffs, furloughs, and reduced newsroom sizes[15][20]. These restrictions have had an impact on both the quantity and quality of news coverage, as fewer journalists are now charged with covering increasingly complicated global events[21][22]. The closure of local news outlets, in particular, has resulted in the formation of "news deserts," or places with little to no local news coverage, aggravating the fall in public engagement and civic participation[23].

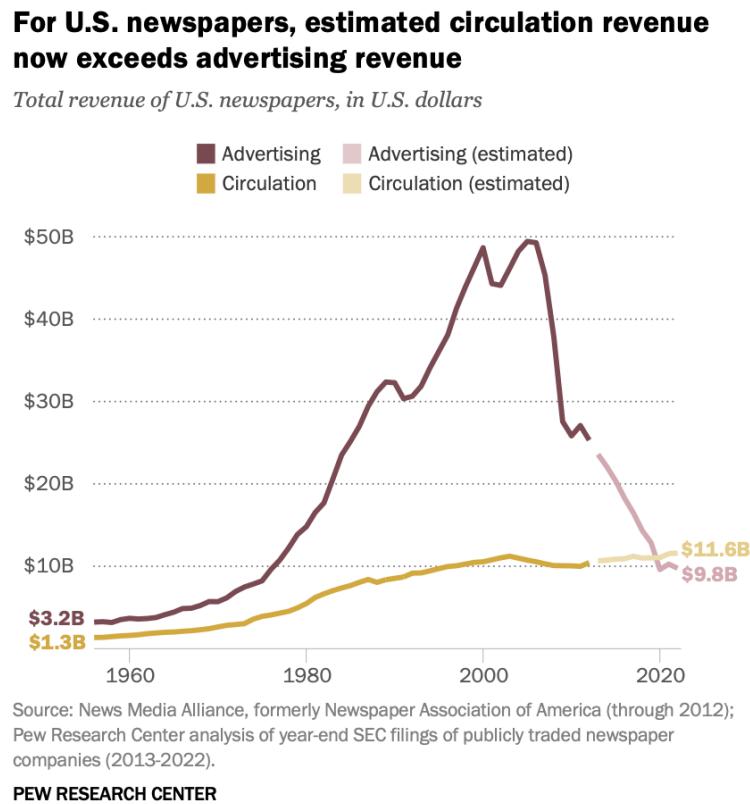


Figure 8: Advertising revenue for newspapers has continued to decline steadily

In response to economic difficulties, several news organizations have turned to technological solutions, such as Large Language Models (LLMs), to streamline processes and cut expenses. LLMs have the ability to automate mundane reporting activities, freeing journalists to work on more sophisticated and investigative projects. However, relying on LLMs has ethical and practical difficulties, such as the risk of misrepresentation, the deterioration of journalistic integrity, and further displacement of journalistic labor[24].

2.4 The Potential Role of Large Language Models in Journalism

The integration of Large Language Models (LLMs) into journalism represents a pivotal moment in the evolution of media and information dissemination. Opportunities Presented by LLMs in journalism include automation and efficiency, which promise to enhance the efficiency of news production through the automation of routine reporting tasks. Automated content generation, par-

ticularly for data-driven stories such as financial reports or sports results, can free up human journalists to focus on in-depth investigations and nuanced storytelling. This shift could lead to a more dynamic allocation of journalistic resources, where human creativity and analytical skills are prioritized over repetitive tasks[25][26]. Additionally, LLMs have the potential to expand coverage to underreported areas and topics, filling the void left by the decline of local news outlets and providing communities with access to relevant news and information[25]. This expanded coverage is crucial for fostering informed citizenry and enhancing public engagement with local issues. Furthermore, LLMs can significantly boost the productivity of newsrooms by streamlining the content creation process, enabling journalists to produce more content within the same time frame[25][26]. This increased productivity could be particularly beneficial in the context of breaking news, where speed and accuracy are paramount.

However, the integration of LLMs into journalism also presents challenges and concerns. Accuracy and misinformation are significant issues, as LLMs can generate coherent and grammatically correct text but their understanding of factual accuracy is limited. The potential for LLMs to inadvertently generate or amplify misinformation is a significant concern[27]. This challenge is exacerbated by the models' susceptibility to biases present in their training data, which can lead to skewed or inaccurate representations of events and issues[28]. Additionally, there is a concern that the widespread use of LLMs could lead to a loss of the human touch that characterizes impactful journalism[25][26]. The nuances of human experience and the depth of investigative reporting may be difficult to replicate through automated processes, potentially leading to a homogenization of news content.

Economic pressures and job displacement are also critical issues, as the reliance on LLMs for content generation could lead to a reduction in the demand for human journalists[25][29]. This shift could exacerbate the economic pressures facing the journalism industry, contributing to further layoffs and the consolidation of media power in the hands of a few technology companies. Moreover, the development and deployment of LLMs are currently dominated by a handful of technology companies, raising concerns about the influence these entities may wield over the journalistic landscape[29][30]. The proprietary nature of these models and the lack of transparency in their training and operation could lead to a situation where the priorities and interests of technology companies overshadow journalistic integrity and independence.

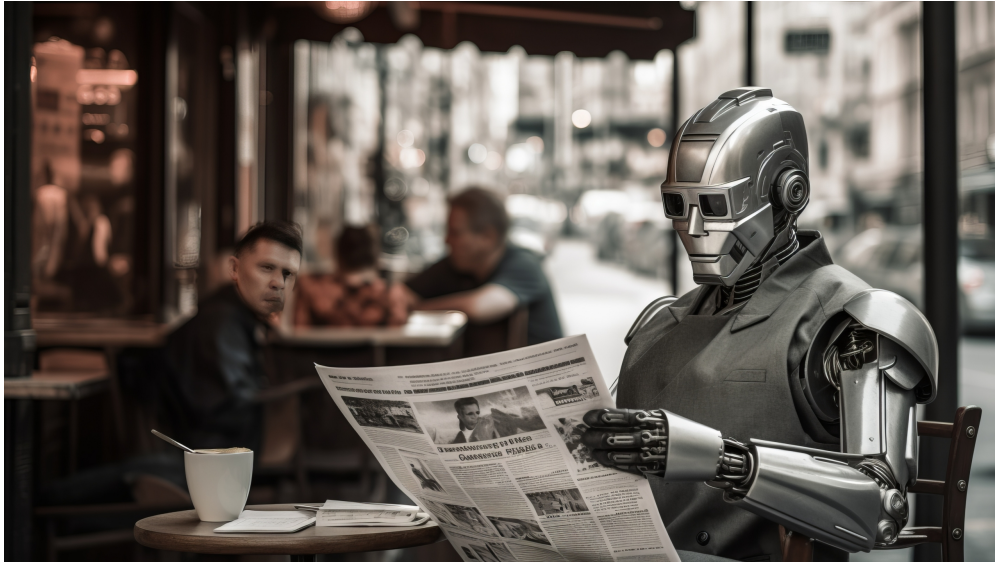


Figure 9: Photograph of a robot reading the newspaper at a cafe

The integration of Large Language Models (LLMs) into journalism is unfolding within a complex social context marked by significant challenges such as the decline of local news outlets, the rise of media manipulation and disinformation, and the economic pressures reshaping the journalism landscape. These issues not only underscore the vulnerabilities within the current media ecosystem but also highlight the potential transformative role of LLMs in addressing some of these challenges. While LLMs offer promising solutions like enhancing news production efficiency and filling coverage gaps, they also introduce risks such as the potential for generating misinformation and further economic disruption in the journalism sector. As we move forward, it is crucial for stakeholders in the journalism and technology sectors to collaborate on developing ethical guidelines and robust frameworks to ensure that the deployment of LLMs contributes positively to the public discourse and upholds the integrity of journalism. This collaborative approach will be essential in harnessing the capabilities of LLMs while mitigating their risks, thereby supporting a resilient and dynamic journalistic landscape.

3 Technical De-mystification

3.1 Background

Humans excel at storytelling, a vital skill for journalism. A seasoned journalist gathers facts from various sources, such as police reports, eyewitness accounts, and social media updates, and

weaves them into a coherent and engaging narrative. This ability to blend different pieces of information into a compelling story showcases our exceptional talent for creating rich, contextually nuanced journalism that resonates deeply with readers. Now, let's delve into the realm of AI and how NLP plays a crucial role in this field.

Initially, computer scientists aimed to create machines that could emulate human thinking and reasoning in every aspect. However, the complexity of this task led to the development of specialized AI fields, with NLP emerging as a crucial area for teaching computers to understand and generate human language. NLP allows computers to interpret and respond to human language, making interactions with technology more intuitive. One of the rapidly evolving fields within AI is Generative AI, which focuses on creating new content by learning from vast amounts of existing text, such as news articles, books, and other written material. This enables computers to generate new articles, stories, or even poetry that resemble the style and content of the examples they studied.

3.2 Overview of Generative AI

Generative AI is a sub-type of AI that can create new content such as text, images, music, and videos. It works by learning from large datasets and then using that knowledge to generate something new. For example, ChatGPT can have conversations, answer questions, and write essays, while DALL-E can draw pictures based on descriptions provided by people. Generative AI assists with creative tasks, helping writers brainstorm new ideas, inspiring artists, and aiding musicians in composing original pieces. By acting as a helpful assistant, generative AI simplifies creative processes, leveraging its vast data knowledge to generate interesting content, making it a powerful tool in various creative fields.

3.3 Towards Journalism

Generative AI is revolutionizing journalism by using AI to create, produce, and analyze content. To make it easier to understand, let's break it down into a few key areas where generative AI is making an impact in journalism:

1. **Content Generation:** Generative AI can automatically create news articles, reports, summaries, or other forms of journalistic content. Think of it as a very smart computer program that can write like a human. It can take large amounts of information, understand it, and then produce a written piece that is coherent and relevant to the context. For example, if there is a sports event, generative AI can write a summary of the game by analyzing the data from the match, mimicking the writing style of human journalists.

2. **Data Analysis and Insights:** Generative AI can also analyze huge datasets to identify patterns and extract meaningful insights for journalists. This means that AI can look at large amounts of data, like financial reports or social media trends, and find interesting stories or important information that journalists might miss. For example, during an election, generative AI can analyze social media posts to see what issues voters are talking about the most.
3. **Newsroom Automation:** Generative AI helps automate various tasks in the newsroom. This includes things like transcribing interviews, translating content into different languages, checking facts, and recommending content. By automating these repetitive tasks, generative AI allows journalists to focus on more important work, like investigating and reporting stories. For example, AI can quickly transcribe an interview, saving journalists hours of manual typing.
4. **Audience Engagement:** Generative AI can personalize news delivery and engage audiences in new ways. It can recommend articles based on what readers have previously read, create interactive stories that respond to readers' choices, and tailor news content to individual preferences. For instance, if you often read about technology, generative AI can suggest more tech-related articles to you.

These different uses of generative AI highlight its diverse role in journalism, covering everything from writing articles to engaging with readers. By understanding these applications, we can appreciate how generative AI is transforming the field of journalism, making it more efficient and personalized.

3.4 Limitations and Challenges

Generative AI in journalism, while powerful, comes with significant limitations and challenges. Accuracy is a major concern, as AI-generated content may not always be reliable, potentially leading to misinformation if the data is misinterpreted. Moreover, AI lacks true contextual understanding, which can result in errors that human journalists would typically avoid, such as missing cultural nuances or context-specific details. Bias is another critical issue; AI systems can inadvertently replicate the biases present in their training data, leading to unfair or skewed content. Additionally, there are ethical concerns related to the displacement of human journalists and the broader implications of over-reliance on AI for news production. Responsible use of generative AI requires careful consideration of these challenges to ensure that it enhances rather than undermines the quality and integrity of journalism.

4 History of the Technology

4.1 Early Beginnings and Statistical Models

The 1960s saw the introduction of ELIZA [31], a ground-breaking chatbot created by MIT researcher Joseph Weizenbaum, which completely changed the field of natural language processing (NLP). The first system to simulate a conversation was ELIZA, a rule-based system that ignited interest in natural language processing (NLP) in the early days [32]. As time passed, IBM led the development of statistical language models in the 1980s, which signaled the start of a new era. By utilizing word occurrence probabilities from large datasets, these models predicted the subsequent word in a sentence and established the stage for further developments [33].

The development of machine learning techniques and the expansion of computational power in the late 1980s caused a dramatic change in natural language processing (NLP). During this period, neural networks were developed, which completely changed the field by enabling models to learn from data on their own instead of depending on preset rules [33]. In addition, the launch of Google Brain in 2011 helped NLP reach new heights by providing the necessary computational power and large datasets to advance language systems development [32].

4.2 From LSTM to Transformers: The Evolutionary Path to Large Language Models

Sepp Hochreiter and Jurgen Schmidhuber's introduction of Long Short-Term Memory (LSTM) networks [34] in the early 1990s represented a major breakthrough in NLP. Long short term memory (LSTM) networks were created to tackle a big problem with earlier neural networks, which struggled to remember information over long sequences. Because of this improvement, LSTMs are much better at understanding and working with languages. This makes them very effective for tasks like translating languages, analyzing sentiment in text, and predicting what comes next in a sentence.

The Transformer model, launched in 2017, played a key role in developing Large Language Models (LLMs). It introduced a new method for computers to understand language by using a setup where one part prepares the information and another part uses it to respond. It also includes special techniques to focus on important parts of the language, much like how humans pay more attention to certain words or phrases when we listen or read. This made it much faster and more efficient than older models like LSTMs. Because of this improvement, models like BERT and OpenAI's GPT series became possible.

- **BERT [35]:** Introduced in 2018, gained attention for its ability to understand word context by looking at text in both directions. Using self-supervised learning, it became a popular tool for natural language processing tasks and even helped improve Google Search for English-language queries.
- **GPT series:** Including GPT-1, GPT-2, and GPT-3, demonstrated the effectiveness of extensive pre-training. Pre-training involves training these models on large amounts of text before they are used for specific tasks. This helps them learn the structure and nuances of language, enabling them to generate human-like text and perform well on various language-related tasks. These models, trained on huge amounts of text, can generate human-like text and are highly adaptable across various language tasks.

4.3 Emergence of Generative AI in Big Tech: A Paradigm Shift

The release of ChatGPT in 2022 was a turning point that led to a general obsession with the idea that generative AI may completely change the way that media is created and consumed. This system attracted notice fast; in just two months after its inception, it had 100 million users. It could produce various forms of content based on prompts. Large tech companies quickly joined the battle with their own AI models OpenAI's GPT, Microsoft's Copilot, Anthropic's Claude, Google's Bard and Gemini, and Meta's open-source LLaMA. Furthermore, generative AI has been used in new search products like Perplexity, browser experiences like Arc, and transformative interfaces like Adobe's Firefly and Photoshop, which have changed how users interact with information.

Even though generative AI has been around since 2018, its unexpected capabilities in late 2022 encouraged its incorporation into other goods and offered a plethora of new experiences and productivity potential. But this technical breakthrough also brought up questions about information authenticity, provenance, source attribution, and the increased possibility of disseminating false information.

4.3.1 Infrastructure Foundations for Building LLMs

High-performance computing clusters are usually the source of the substantial computational resources needed for training large language models. These clusters are made up of thousands of servers that have strong CPUs, GPUs, or TPUs. Training process acceleration is frequently achieved with the use of specialized hardware accelerators, such as TPUs. By using distributed training frameworks such as TensorFlow and PyTorch, firms may divide up the training process among several servers or GPUs in the cluster. Efficient communication between servers is made possible by high-speed interconnects like Ethernet and InfiniBand. Massive dataset handling storage infrastructure is critical, and cloud storage and HDFS are two popular solutions used to do

this. The stability and effectiveness of the training infrastructure are guaranteed by the use of monitoring and management tools, which are used to measure metrics, control work scheduling, and diagnose problems in real-time.

4.3.2 Common Crawl Dataset: Uniting Forces to Capture the Web's Essence

The Common Crawl dataset [36], spanning terabytes of data, represents one of the most extensive collections of online information, extracted from billions of web pages. Acquired by the crawler on a monthly basis, new data files are periodically released, ensuring that the dataset remains current and comprehensive. This vast resource serves as the foundation for a variety of prominent language models, including GPT-3, LLaMA, OpenLLaMA, and T5, underscoring its critical role in the field of natural language processing (NLP).

The creation and maintenance of the Common Crawl dataset are powered by a coalition of diverse partners, including DuckDuckGo, Amazon, Ai2, Hugging Face, the Linux Foundation, and Nvidia. This collaborative effort transcends traditional boundaries, offering unrestricted access to a treasure trove of digital content. The dataset's openness and scale make it a pivotal resource for researchers and developers aiming to push the boundaries of AI and machine learning.

4.4 Derivative Datasets and Specific Applications

Several specialized datasets, such as RefinedWeb, C4, ROOTS, and Red Pajama, have been derived from Common Crawl to address specific needs within the NLP community. These derivatives illustrate the flexibility and adaptability of the Common Crawl data for various applications, from training sophisticated language models to exploring the intricacies of human language and digital communication.

4.4.1 Colossal Clean Crawled Corpus (C4)

The C4 dataset [37], a refined version of Common Crawl data, exemplifies the process of filtering and enhancing raw web data to better serve NLP purposes. The creation of C4 involved meticulous filtering to exclude non-English text, offensive content, and low-quality placeholders like "Lorem ipsum." However, this filtering process also underscored the challenges and potential biases inherent in such practices [38].

4.4.2 RefinedWeb

Falcon RefinedWeb [39] is a large collection of English web content developed by TII, created by carefully selecting and cleaning data from CommonCrawl. This process helps in building models that perform as well or better than those trained on specially selected datasets. The dataset contains a vast amount of text, equivalent to 500-650GB, and expands to about 2.8TB when unpacked. It's a valuable resource for training advanced language models and can be used alone or alongside other curated sources. Falcon RefinedWeb has been essential in training top-performing Falcon models and has many potential uses in natural language processing. It is available under a free-to-use license and follows the CommonCrawl usage guidelines.

4.4.3 ROOTS

This dataset [40] consists of curating a web-scale dataset that covers 59 languages, including 46 natural languages and 13 programming languages. The selection of languages was primarily influenced by the participating communities, emphasizing the importance of language expertise. Our final corpus comprises two main components: 62% of the text comes from a community-selected and documented list of language data sources, which we describe in section 2, and 38% consists of text extracted from a pre-processed web crawl, OSCAR [41], filtered with the assistance of his group.

4.5 Generative AI in Journalism

As people have started incorporating Generative AI, like Large Language Models (LLMs), into their respective domains such as healthcare, logistics, financial technology, and science, the landscape of these industries has begun to shift dramatically. In healthcare, LLMs are revolutionizing patient care through advanced diagnostics, personalized treatment plans, and predictive analytics. Logistics companies are leveraging LLMs to optimize supply chain operations, enhance route planning, and improve inventory management. In fintech, LLMs are being utilized for fraud detection, risk assessment, and algorithmic trading, leading to more efficient and secure financial transactions. Similarly, in the field of science, LLMs are aiding researchers in data analysis, hypothesis generation, and literature review, accelerating the pace of discovery across various disciplines. Likewise in the Journalism field, people will make use of LLMs for making automated content creation, fact checking and news delivery, personalized news delivery, enhanced storytelling and Real time reporting. As these industries continue to harness the power of Generative AI, the possibilities for innovation and transformation are seemingly boundless.

In 2023, the news industry embarked on a transformative journey, grappling with the implications of generative AI such as news gathering and news distribution, on every facet of its operation. This period of adaptation was marked by a collective effort to understand how AI could revolutionize news gathering, production, distribution, and business models. Key initiatives such as the Generative AI in the Newsroom (GAIN) project, funded by the Google News Initiative, the AI, Media, and Democracy Lab supported by the Knight Foundation, and the Open Society Foundation AI in Journalism Challenge, played a pivotal role in fueling this exploration. Surveys conducted by esteemed institutions like WAN-IFRA and the Associated Press further contributed to shedding light on both the potential and challenges presented by generative AI.

According to the paper published by Nicholas Diakopoulos on "Generative AI in Journalism"[42], a survey encompassing 292 news industry professionals unveiled a majority who possessed a solid understanding of generative AI, with many already integrating it into their workflows to varying extents. Noteworthy was the fact that these respondents boasted an average of 18 years of experience in the field, underlining the importance of seasoned professionals navigating the evolving media landscape shaped by generative AI.

4.5.1 Key Datasets Driving Generative AI in Journalism

Datasets play a crucial role in the development and application of generative AI in journalism. These datasets serve as the foundation upon which AI models are trained to understand language, context, and journalistic conventions. Here are some key types of datasets used in this field:

- **News Corpus:** Large collections of news articles from various sources and domains form the backbone of many AI models in journalism. These datasets cover a wide range of topics, including politics, sports, entertainment, science, and more. Examples of news corpora include the Reuters Corpus, the New York Times Annotated Corpus, and the Common Crawl dataset.
- **Fact-Checking Databases:** Datasets containing verified facts and claims, along with their sources, are essential for training AI models to identify and verify information in news articles. Fact-checking databases such as ClaimBuster, PolitiFact, and FactCheck.org provide valuable resources for this purpose.
- **Multimodal Datasets:** With the increasing popularity of multimedia content in journalism, datasets combining text, images, and videos have become important for training AI models to analyze and generate multimedia news stories. Examples include the MS-COCO dataset for image captioning and the How2 dataset for multimodal machine translation.
- **Fake News Datasets:** Datasets containing examples of fake news articles, along with corresponding fact-checked labels, are used to train AI models to detect misinformation and

disinformation. Examples include the FakeNewsNet dataset and the LIAR dataset.

- **Social Media Data:** Social media platforms serve as important sources of news and information, making datasets derived from social media valuable for training AI models in journalism. Platforms like Twitter, Reddit, and Facebook provide APIs for accessing public data, which can be used to create datasets for sentiment analysis, trend detection, and more.
- **User Interaction Data:** Datasets containing user engagement metrics, such as clicks, likes, shares, and comments, are used to train AI models to personalize news content and optimize user experience. These datasets help algorithms understand user preferences and behavior patterns.
- **Annotated Corpora:** Datasets annotated with linguistic features, such as named entities, sentiment labels, and discourse structures, are valuable for training AI models in natural language understanding and generation tasks specific to journalism. Examples include the CoNLL datasets and the Penn Treebank.
- **Historical Archives:** Digitized archives of historical newspapers, magazines, and other print media provide valuable datasets for training AI models in historical journalism research and analysis. These datasets enable researchers to explore trends, events, and cultural phenomena over time.

5 Privacy Analysis

5.1 Theoretical Framework of Consent

Consent, in the realm of generative AI and journalism, refers to the explicit approval given by individuals or entities allowing their data to be used for training, developing, and deploying AI models. This principle is fundamental to safeguarding personal autonomy, privacy, and ensuring accountability in the handling of data. In journalism, this means that any data used by AI to generate content should be sourced with the clear and informed consent of the data owners, ensuring that their rights and interests are respected and protected.

In the fast-changing field of digital journalism, consent is essential for managing the ethical and legal challenges associated with data usage. Fundamentally, consent involves explicit approval by individuals or entities for the use of their data in specific ways. This principle protects personal autonomy, privacy, and ensures accountability in handling data.[43]

The implementation of consent protocols faces significant obstacles when applied to the domain of Large Language Models (LLMs). LLMs, like the GPT series from OpenAI, are trained

on extensive datasets that include a variety of data types such as text, images, and audio. These datasets are crucial for training AI to understand language patterns, generate text, and execute tasks with precision akin to human ability.[44]

Gaining explicit consent for using such broad datasets is particularly challenging within the framework of LLMs. Traditional methods of obtaining consent for specific data uses are inadequate due to the vast scope and diversity of the data involved. Additionally, the continual collection of data from public sources makes it difficult to track the origin of the data and the individuals associated with it, complicating the enforcement of consent protocols.[42] This raises the question: does this show that there isn't a way to scale it ethically?

One promising direction is to conceptualize consent as a dynamic, context-based process rather than a one-time agreement at the point of data collection. This model would emphasize continuous transparency, empowerment of users, and active engagement throughout the data lifecycle [45]. [42] For instance, in the case of the Common Crawl dataset, implementing a dynamic consent model could involve regularly updating data sources about how their data is being used and providing mechanisms for data contributors to review and manage their consent preferences. This approach, while challenging, could potentially align the scale of data usage with ethical consent practices.

Furthermore, specific technologies can be leveraged to preserve privacy and improve consent practices in generative AI applications within journalism. Federated learning, for example, allows AI models to be trained on data across multiple devices or newsrooms without transferring the raw data to a central server. This approach minimizes privacy risks by keeping data localized within each newsroom. Differential privacy techniques can add noise to datasets to obscure individual data points while still providing useful aggregate data for AI model training, ensuring that journalists' and sources' identities remain protected. Blockchain technology can be used to manage consent records immutably, ensuring that journalists' consent choices regarding their content are transparent and verifiable over time. Implementing these technologies requires a collaborative effort from AI developers, media organizations, legal experts, and policymakers to ensure they are both practical and effective in real-world journalism applications[46].

However, it is crucial to consider the limitations and practical challenges of these technologies. For example, federated learning's effectiveness depends on the availability of sufficient computational resources within newsrooms and robust communication protocols between them. Differential privacy's added noise can sometimes degrade the utility of the data, making it less effective for certain journalistic applications where data accuracy is critical. Blockchain, while offering transparency and immutability, faces scalability issues and energy consumption concerns. These considerations highlight the complexity of implementing these technologies at scale in the

journalism industry and the necessity for ongoing research and development to optimize their use in preserving privacy and consent in the context of generative AI in journalism. [42]

Overall, addressing consent in the context of LLM data usage demands a comprehensive strategy that respects the complex nature of AI technologies while maintaining core values of privacy, autonomy, and ethical data management. For example, while federated learning allows AI models to be trained across multiple newsrooms without transferring raw data to a central server, thereby preserving the privacy of journalists and their sources, differential privacy adds noise to datasets to obscure individual data points, protecting sensitive information while still enabling effective AI model training, to reiterate from the previous section, blockchain technology can immutably manage consent records, ensuring that journalists' and news organizations' consent choices regarding their content are transparent and verifiable over time. [47] Implementing these technologies would require collaborative efforts from AI developers, media organizations, legal experts, and policy-makers to ensure they are practical and effective. However, it is essential to acknowledge that the integration of these technologies must be part of a larger ethical framework that includes transparent communication, continuous monitoring, and a commitment to addressing power imbalances between journalists and AI developers. This comprehensive approach can help create a balanced data ecosystem that aligns innovation with individual rights and societal interests, thereby fostering trust and ethical practices in AI-driven journalism.[42]

5.2 Understanding Compensation in Generative AI in Journalism

Compensation, in the context of generative AI in journalism, refers to the equitable remuneration provided to content creators, such as journalists and media organizations, for the use of their copyrighted materials by AI developers. As AI technologies become more sophisticated, they often rely on vast amounts of data, including news articles, images, and other media, to train their models. This practice raises significant ethical, economic, and legal questions about whether and how the original creators should be compensated for the use of their intellectual property.[48]

The core issue revolves around the balance between fostering innovation in AI and ensuring that the rights and labor of content creators are respected. Journalists invest substantial time and resources into producing high-quality content. When this content is used without permission or proper compensation, it not only infringes on their intellectual property rights but also undermines their financial viability. This issue is compounded in the digital age, where content is easily accessible and reproducible, making it challenging to enforce traditional copyright protections.[48]

In journalism, compensation models might include licensing agreements, royalties, or collective licensing organizations that ensure fair distribution of revenues to all contributing media

outlets. These models aim to sustain the journalistic enterprises that provide the foundational content for AI technologies, thereby preserving the integrity and sustainability of the journalism industry.[49]

5.2.1 Case Study: OpenAI vs New York Times

The ongoing legal battle between The New York Times and OpenAI exemplifies the challenges surrounding data consent and compensation in AI-driven journalism. The New York Times alleges that OpenAI utilized its copyrighted material without permission for training its AI models[50]. This case highlights the necessity for clear consent mechanisms and fair compensation practices in AI training, especially concerning journalistic content.

At the heart of the lawsuit is the question of whether using copyrighted material for AI model training constitutes a violation of intellectual property rights and whether appropriate compensation should be provided to content creators. The New York Times argues that OpenAI's use of its content without explicit consent and compensation constitutes infringement, underscoring the need for robust consent mechanisms to protect media organizations' intellectual property in the digital realm[51].

The implications of this lawsuit are profound and multifaceted. On a legal level, a ruling in favor of The New York Times could establish a precedent that mandates explicit consent and fair compensation for the use of copyrighted content in AI training. Such a precedent would likely necessitate significant changes in how AI companies source their training data, potentially leading to the development of more rigorous consent protocols and compensation structures[51]. [50]

From an ethical standpoint, the case emphasizes the moral responsibility of AI developers to acknowledge and remunerate the labor of content creators. The unauthorized use of journalistic content not only deprives journalists of rightful earnings but also undermines the ethical foundation upon which journalism is built. The erosion of this foundation could have long-term repercussions for public trust in both journalism and AI technologies.

Moreover, the outcome of this legal battle has broader implications for the AI domain, particularly in the context of journalistic content. A favorable ruling for The New York Times could set a precedent for how consent and compensation must be handled in AI-driven applications, potentially shaping future regulatory frameworks and industry practices. It could also prompt AI developers to reassess their data sourcing strategies and implement more stringent consent and compensation mechanisms to mitigate legal risks and uphold ethical standards[52]. [50]

The case raises critical questions about the sustainability of journalism in the digital age.

Without fair compensation, media organizations may struggle to maintain financial viability, ultimately affecting the quality and diversity of news content available to the public. This case underscores the urgent need for ethical and legal standards that ensure AI development does not come at the expense of journalistic integrity and sustainability.

5.2.2 Case Study: The Intercept, Raw Story, and AlterNet vs. OpenAI and Microsoft

In February 2024, three progressive US outlets—The Intercept, Raw Story, and AlterNet—filed lawsuits against OpenAI and Microsoft, alleging copyright infringement. The lawsuits claim that OpenAI and Microsoft used their copyrighted articles to train ChatGPT without permission or proper attribution, violating the Digital Millennium Copyright Act [53]. This case further illustrates the challenges of ensuring consent and compensation in AI-driven journalism.

The lawsuits assert that OpenAI stripped copyright management information (CMI) from the articles, preventing ChatGPT from acknowledging or attributing the original authors when generating content based on those works. This practice allegedly enabled OpenAI to use the journalistic content without compensating the news organizations, further undermining their financial viability in an already struggling industry [53] [54].

The plaintiffs argue that the removal of CMI and the unauthorized use of their content by AI models like ChatGPT not only constitute copyright infringement but also threaten the sustainability of independent journalism. By failing to respect copyright laws, OpenAI and Microsoft are accused of profiting from the hard work of journalists without providing due credit or compensation, exacerbating the financial challenges faced by news organizations [53][54][55].

The lawsuits seek damages and profits from OpenAI, as well as an injunction requiring the removal of the plaintiffs' copyrighted works from OpenAI's training datasets. The outcomes of these cases could set significant precedents for the AI industry, particularly concerning the ethical and legal use of copyrighted materials in training AI models [53][54][55].

These cases highlight a critical tension between technological innovation and ethical standards. On one hand, AI technologies like ChatGPT hold immense potential to transform industries, including journalism, by automating tasks and generating content. On the other hand, the foundation of such technologies must be ethically sound, respecting the rights and contributions of content creators. The failure to address this tension could lead to a future where technological advancements are marred by legal battles and ethical controversies.

5.3 Implications of Using Public Data Without Explicit Consent

The unauthorized use of public data without explicit consent in generative AI for journalism raises profound ethical and societal concerns. Central to these concerns is the erosion of public trust in media produced by AI. When audiences are unaware of how their data is being used and whether appropriate consent has been obtained, it undermines the integrity and authenticity of the content they consume. This lack of transparency regarding data usage practices can lead to skepticism and suspicion among audiences, ultimately threatening the credibility of news organizations[56].

Moreover, the proliferation of AI-generated content exacerbates issues related to misinformation and bias. Without clear guidelines and oversight mechanisms, AI models may inadvertently propagate false or misleading information[57]. This can have far-reaching consequences for public discourse and democratic processes, as misinformation can shape public opinion and influence decision-making. In the context of journalism, where accuracy and trust are paramount, the ethical lapses in data handling can severely undermine the role of media as a reliable information source.

Addressing these ethical and societal concerns requires a concerted effort from AI developers, news organizations, and regulatory bodies. Transparency about data usage practices, including how public data is sourced and utilized, is essential for building and maintaining public trust. AI developers need to implement measures that ensure their models are trained on ethically sourced data, and news organizations must advocate for policies that protect their content. Additionally, mitigating the risk of bias and misinformation in AI-generated content involves algorithmic audits, incorporating diverse data sets, and continuous monitoring to detect and correct inaccuracies[47].

Additionally from a legal standpoint, the unauthorized use of copyrighted material without consent carries significant implications for AI developers. Copyright infringement lawsuits, such as the ongoing cases involving The New York Times and The Intercept, can result in extensive litigation and substantial financial liabilities [58]. The potential for costly legal battles and damages awards can deter investment in AI technologies and hinder their commercial viability in journalism and other sectors.

Furthermore, the reputational damage resulting from legal disputes can tarnish the image of AI companies and deter potential partners and customers. Trust and credibility are paramount in the AI industry, and allegations of copyright infringement or data misuse can severely undermine confidence in AI technologies. This erosion of trust can have long-term consequences for the growth and adoption of AI, as stakeholders may become wary of engaging with technologies perceived as ethically or legally dubious[59].

To mitigate these legal and commercial risks, AI developers must prioritize compliance with

copyright laws and data ethics standards. This includes obtaining appropriate permissions for data usage, respecting intellectual property rights, and implementing robust data governance practices. By proactively addressing these issues, AI companies can safeguard their reputation and maintain trust with stakeholders[60] [42]. Moreover, companies must invest in educating their teams about ethical data usage and the importance of maintaining high standards of data integrity. [48]

In addition, AI developers should engage in proactive dialogue with media organizations and other stakeholders to establish mutually beneficial agreements for data use. This collaborative approach can help develop frameworks that balance innovation with the protection of intellectual property rights, ensuring that AI development does not come at the expense of content creators. Ultimately, the ethical implications of using public data without explicit consent highlight the need for a paradigm shift in how AI development intersects with journalism. The industry must move towards a model where ethical considerations are embedded in the design and deployment of AI systems. This includes not only respecting the rights of data subjects but also fostering a culture of accountability and responsibility among AI developers. By fostering a culture of respect and collaboration, the industry can navigate the complex legal landscape more effectively and sustainably. [59] [47]

6 Power & Justice Analysis

The integration of Large Language Models (LLMs) into journalism represents a significant technological shift with profound implications for power dynamics within the media industry. This section explores how LLMs shift power, the systems of classification they rely on, their potential biases, and the broader societal impacts. By examining these factors, we aim to provide a comprehensive analysis of the justice implications of deploying LLMs in journalism.

6.1 Systems of Classification and Ethical Considerations

Large Language Models (LLMs) operate on intricate systems of classification that categorize and interpret vast amounts of textual data. These systems are built on training datasets that include diverse sources such as news articles, social media posts, and other publicly available texts. However, the ethicality of these classification systems is questionable due to several factors. The datasets used to train LLMs often lack representation from marginalized communities. This exclusion can lead to biased outputs that do not accurately reflect the experiences and perspectives of these groups. For instance, if the training data predominantly includes content from Western media, the LLM may produce outputs that are skewed towards Western viewpoints, neglecting the voices of non-Western communities. This lack of representation can perpetuate a cycle of ex-

clusion, where the perspectives of marginalized groups are continually underrepresented in media outputs generated by LLMs.

The inherent biases in the training data can perpetuate stereotypes and reinforce existing power imbalances. For example, if the data includes biased language or discriminatory content, the LLM may generate outputs that reflect these biases, thereby perpetuating harmful narratives[61]. Studies have shown that LLMs can exhibit gender, racial, and cultural biases, which are often a reflection of the biases present in the training data[62]. For instance, if the majority of the data portrays women in stereotypical roles, the LLM is likely to generate outputs that reinforce these stereotypes, thus contributing to the perpetuation of gender bias. The deployment of LLMs in journalism can have a disparate impact on different groups. Automated content generation may disproportionately affect journalists from underrepresented backgrounds who may already face barriers in the industry. The reliance on LLMs could exacerbate these disparities by reducing opportunities for these journalists to contribute their unique perspectives[63]. This can lead to a homogenization of news content, where diverse voices and viewpoints are marginalized, further entrenching existing inequalities in the media landscape.

The ethical implications of the classification systems used by LLMs are profound. These systems often operate without transparency, making it difficult to understand how decisions are made and what biases may be influencing the outputs. This lack of transparency can undermine public trust in the media and in the technologies that support it[64]. Moreover, the use of LLMs raises questions about accountability. When biased or harmful content is generated, it is often unclear who is responsible: the developers of the LLM, the organizations that deploy it, or the users who interact with it[65]. To address these ethical concerns, it is crucial to implement measures that ensure fairness and mitigate bias in LLMs. This includes diversifying the training datasets to include a broader range of perspectives and experiences, particularly from marginalized communities[66]. Additionally, employing techniques such as Uncertainty Quantification (UQ) and Explainable AI (XAI) can help identify and mitigate biases in LLM outputs[67]. These techniques provide insights into whether LLMs are appropriately focusing on a task or if biases are swaying their outputs, thereby enhancing the fairness and transparency of the models.

The systems of classification used by LLMs in journalism have significant ethical implications. The exclusion of marginalized communities, the perpetuation of biases, and the disparate impact on underrepresented groups highlight the need for a more inclusive and transparent approach to the development and deployment of LLMs. By addressing these ethical concerns, we can work towards a more equitable and just media landscape that accurately reflects the diversity of human experiences.

6.2 Shifting Power Dynamics

One of the primary shifts is the concentration of corporate power. The development and deployment of LLMs are predominantly controlled by a few large technology companies, such as OpenAI, Google, and Microsoft. This concentration of power raises concerns about the influence these companies may wield over the journalistic landscape. The proprietary nature of LLMs and the lack of transparency in their operation can lead to a situation where the priorities and interests of technology companies overshadow journalistic integrity and independence. This dynamic can result in a media environment where the content and narratives are subtly shaped by corporate interests rather than journalistic principles[68].

Another significant shift is related to economic resources. The development and maintenance of LLMs require substantial computational power and large datasets, which are expensive to acquire and manage. This high cost can divert resources from other potential solutions, particularly for smaller news organizations that may struggle to compete with larger entities capable of investing in these technologies. As a result, there is a risk of further consolidation of media power, where only well-funded organizations can afford to leverage LLMs, potentially marginalizing smaller, independent news outlets. This economic barrier can exacerbate existing inequalities within the media industry, limiting the diversity of voices and perspectives available to the public[69][70].

Labor displacement is another critical issue arising from the integration of LLMs in journalism. The automation of routine reporting tasks through LLMs can lead to job displacement for journalists, particularly those involved in tasks that LLMs can easily replicate, such as writing financial reports or summarizing sports scores. This shift not only affects the economic stability of individual journalists but also has broader implications for the diversity and quality of news coverage. The reduction in human journalists can lead to a homogenization of news content, as LLMs may lack the nuanced understanding and investigative skills that human journalists bring to their work. Moreover, the displacement of journalists can reduce the overall capacity for investigative journalism, which is crucial for holding power to account and providing in-depth analysis of complex issues[71][68].

The reliance on LLMs in journalism can shift the power dynamics between journalists and their employers. Journalists may find themselves increasingly dependent on LLMs for their work, which can alter the nature of their roles and the skills required. This shift can lead to a devaluation of traditional journalistic skills and an increased emphasis on technical skills related to managing and interacting with LLMs. As a result, journalists may need to adapt to new workflows and develop new competencies, which can be challenging and may not be accessible to all[63].

6.3 Algorithmic Bias and Disparate Impact

Large Language Models (LLMs) are susceptible to various forms of algorithmic bias, which can lead to disparate impacts on different groups. These biases arise from the data used to train the models and the inherent design of the algorithms themselves. The training data for LLMs may be skewed towards certain demographics, leading to biased outputs. For example, if the data predominantly includes content from male authors, the LLM may generate outputs that reflect male perspectives more prominently, marginalizing female voices. This skew in data can result in the underrepresentation of women and other marginalized groups, perpetuating existing societal biases and inequalities[72]. Studies have shown that LLMs often reflect the biases present in their training data, which can include stereotypes and discriminatory language[73][74]. This issue is compounded by the fact that much of the data available on the internet, which is used to train these models, is itself biased[75].

The deployment of LLMs can lead to allocation harms, where certain groups are disadvantaged in terms of access to resources and opportunities. For instance, automated content generation may prioritize topics that are more commercially viable, neglecting important but less profitable issues that affect marginalized communities. This can result in a lack of coverage for issues pertinent to these communities, further marginalizing them and reducing their visibility in public discourse. Additionally, the economic pressures on journalism, exacerbated by the use of LLMs, can lead to job displacement for human journalists, particularly those from underrepresented backgrounds[72].

LLMs can perpetuate representational harms by reinforcing stereotypes and biased narratives. For example, if the training data includes biased portrayals of certain ethnic groups, the LLM may generate outputs that reinforce these negative stereotypes, contributing to social stigmatization and discrimination. This can have serious consequences for the affected groups, including reinforcing harmful societal norms and reducing the diversity of perspectives in media and public discourse[73][72]. Research has shown that LLMs can generate content that is biased against women, different cultures, and sexualities, often associating certain groups with negative or stereotypical roles[72][76].

The biases in LLMs are not just theoretical concerns but have real-world implications. For instance, in healthcare, LLMs have been found to propagate harmful, race-based medical misconceptions, which can lead to incorrect and potentially harmful medical advice[76]. Similarly, in other domains such as hiring and legal decisions, biased LLMs can lead to unfair outcomes for certain groups, perpetuating existing inequalities[73][74]. To mitigate these biases, it is crucial to adopt a multifaceted approach that includes improving the diversity and quality of training data, implementing robust bias detection and mitigation techniques, and ensuring transparency and ac-

countability in the development and deployment of LLMs[77][78][61]. Researchers are exploring various methods to reduce bias in LLMs, such as integrating logical reasoning into models and using fairness indicators to detect and mitigate bias[74][61]. However, these efforts must be ongoing and adaptive to address the evolving nature of biases in AI systems.

While LLMs offer significant potential benefits, their susceptibility to algorithmic bias and the resulting disparate impacts on different groups highlight the need for careful and responsible development and deployment. By addressing these biases, we can work towards creating more equitable and inclusive AI systems that serve the needs of all users.

6.4 Sociotechnical Systems and Power Shifts

The integration of Large Language Models (LLMs) into journalism represents a significant shift in the sociotechnical landscape, altering power dynamics in several profound ways. This transformation is multifaceted, encompassing economic, social, and ethical dimensions that collectively reshape the media industry. One of the primary ways LLMs shift power is through capital accumulation. The automation of content generation by LLMs allows technology companies to significantly reduce labor costs, thereby increasing their profit margins. This process often occurs at the expense of journalists' livelihoods, as fewer human reporters are needed to produce the same volume of content. This dynamic can lead to labor displacement, where journalists, particularly those in precarious employment situations, may find themselves out of work. The economic benefits accrued by technology companies through the deployment of LLMs thus contribute to a form of dispossession, where the value generated by human labor is appropriated by capital owners[79].

Resource diversion is another critical aspect of how LLMs shift power within the journalism industry. The development and maintenance of LLMs require substantial financial and technological resources. These resources are often diverted from other potential solutions that might be more equitable and sustainable. For instance, community-based journalism initiatives and local news outlets, which play a crucial role in fostering democratic engagement and providing diverse perspectives, may suffer from underfunding as investments flow towards more technologically advanced but less inclusive models. This diversion of resources can exacerbate existing disparities in news coverage, particularly in underserved communities that rely heavily on local journalism for information and accountability[79][80].

The deployment of LLMs also impacts access to social, legal, and economic resources. Marginalized communities, which often lack the technological infrastructure and digital literacy required to fully benefit from LLM-generated content, may find themselves further excluded from the information ecosystem. This digital divide can lead to a situation where the benefits of advanced

AI technologies are unevenly distributed, reinforcing existing inequalities. For example, while affluent communities may enjoy enhanced access to personalized and timely news, economically disadvantaged groups may struggle to access even basic information, thereby widening the gap in information equity[79][80].

The integration of LLMs into journalism represents a complex sociotechnical system that shifts power in multiple ways. It contributes to capital accumulation and labor displacement, diverts resources from potentially more equitable solutions, and exacerbates existing inequalities in access to information. Addressing these challenges requires a multifaceted approach that includes ensuring diverse and representative training data, developing ethical guidelines for AI deployment, and fostering collaboration between technologists, journalists, and policymakers. By doing so, we can harness the potential of LLMs while mitigating their risks, thereby supporting a more inclusive and just media landscape.

7 Accountability Analysis

Accountability in the domain of generative AI in journalism refers to the mechanisms and principles that ensure those developing, deploying, and utilizing AI systems are held responsible for their actions and the outcomes of those systems. This comprises a range of practices including transparency, responsibility, ethical adherence, and the establishment of clear lines of accountability for any harm or issues that arise from the use of AI technologies.

7.1 Principles of Accountability of Generative AI in Journalism

Various principles have been suggested to govern and address accountability in AI systems. Key among these are transparency, explainability, responsibility, and fairness. These principles aim to ensure that AI systems operate in a manner that is understandable, justifiable, and aligned with societal values and legal standards.

7.1.1 Transparency and Explainability

Transparency and explainability are fundamental principles for ensuring accountability in the deployment of generative AI within journalism. Transparency refers to the practice of making the processes, data, and decision-making criteria of AI systems visible and understandable to all stakeholders. Explainability, on the other hand, focuses on the ability to articulate how and why an AI system arrived at a particular decision or output. These principles are essential in maintaining public trust, ensuring the accuracy of AI-generated content, and upholding journalistic integrity.[47]

[81]

Transparency in generative AI involves multiple layers, starting with the data used to train AI models. For instance, datasets like Common Crawl, which aggregates vast amounts of web data, need to be scrutinized for their sources and biases. Journalistic entities utilizing these datasets must disclose their origins, the selection process, and any potential limitations or biases inherent in the data. This level of transparency helps in mitigating misinformation and ensuring that the AI-generated content is credible and reliable.[47]

Furthermore, transparency extends to the algorithms and models themselves. News organizations should provide detailed documentation on how their AI systems function, including the algorithms used, the training process, and the criteria for generating content. By doing so, they can demystify the technology for both the journalists who use it and the audiences who consume its outputs. This openness not only builds trust but also allows for external audits and evaluations, enhancing the system's credibility and reliability. [82]

Explainability in generative AI is equally crucial. It involves making the AI's decision-making processes understandable to non-experts. For example, if an AI model generates a news article, it should be able to provide a rationale for why it chose specific facts, the sources it used, and how it constructed the narrative. This is particularly important in journalism, where the accuracy and credibility of information are paramount.[83]

To achieve explainability, AI systems can incorporate features such as traceability of data sources and decision logs that detail the steps taken by the AI during content creation. Techniques such as natural language explanations, where the AI describes its actions in human-readable language, can also be employed. These methods enable journalists and editors to verify the content generated by AI and understand any potential biases or errors that might have influenced the output .[81]

Moreover, explainability empowers journalists to provide accurate attributions and contextual information in their reports, thereby maintaining the integrity of the journalistic process. It also facilitates accountability by making it easier to identify and rectify mistakes, ensuring that AI systems do not operate as opaque black boxes but as transparent tools that enhance journalistic practices .[81]

7.1.2 Responsibility and Fairness

Responsibility and fairness are cornerstone principles in the ethical deployment of generative AI in journalism. These principles ensure that the entities involved in the creation and dissemi-

nation of AI-generated content are held accountable for their actions and that the outputs of AI systems do not perpetuate or exacerbate existing biases and inequalities.[84]

In the context of generative AI in journalism, responsibility involves clearly defining the roles and duties of all stakeholders, including AI developers, news organizations, and individual journalists. Each party must understand their specific responsibilities in ensuring that AI systems are used ethically and effectively. For AI developers, this means designing systems that prioritize ethical considerations, such as data privacy and bias mitigation, from the outset. Developers should implement rigorous testing and validation processes to ensure that AI models perform as intended and do not produce harmful or misleading content . [85]

News organizations, on the other hand, bear the responsibility of overseeing the deployment of AI systems. This includes establishing editorial guidelines that govern the use of AI-generated content, providing training for journalists on how to use these tools responsibly, and ensuring that there are mechanisms in place for monitoring and addressing any issues that arise. For example, if an AI-generated article contains inaccuracies or biases, there should be clear protocols for correcting these errors and informing the public . [86]

Individual journalists also have a role to play in maintaining the ethical use of AI. They must remain vigilant and critical of AI-generated content, verifying facts, and ensuring that the outputs align with journalistic standards. This shared responsibility helps create a robust system of checks and balances that upholds the integrity of the journalism profession .[80]

Fairness in generative AI for journalism is crucial for ensuring that AI systems do not perpetuate existing biases or create new forms of inequality. AI models are trained on large datasets that often reflect societal biases present in the source material. If not carefully managed, these biases can be amplified in the AI-generated outputs, leading to unfair and potentially harmful consequences .

To address this, AI developers must implement strategies to detect and mitigate bias during the training and deployment phases. This can include using diverse datasets that better represent various demographics, implementing algorithmic fairness techniques, and continuously monitoring AI outputs for signs of bias. For instance, employing fairness-aware machine learning algorithms can help in identifying and correcting biases that might otherwise go unnoticed . [86] [42]

News organizations must also commit to fairness by ensuring that AI-generated content is reviewed and edited with a critical eye towards bias. They should establish editorial standards that prioritize balanced and fair reporting, regardless of whether the content is produced by humans or AI. This includes providing transparency about the sources and processes used by AI systems,

which helps in building trust and accountability . [51] [42]

Furthermore, fairness extends to the impact of AI on the journalism profession itself. As AI systems become more prevalent, there is a risk that they may displace human journalists, particularly those in entry-level positions. Ensuring fairness involves creating pathways for journalists to adapt to the changing landscape, such as through training and development programs that equip them with the skills needed to work alongside AI technologies .

7.2 Analyzing Accountability in AI-Driven Journalism

To determine whether these principles sufficiently address the harms or potential harms raised in earlier sections, it is necessary to explore the specific challenges and pitfalls associated with accountability in AI-driven journalism.

7.2.1 Accountability Gaps and Moral Crumple Zones

One of the primary concerns is the creation of accountability gaps. These occur when the responsibility for the actions and outcomes of AI systems is not clearly delineated. In journalism, this can manifest in several ways. For instance, if an AI system generates a misleading article, it can be challenging to determine whether the fault lies with the developers who designed the AI, the journalists who deployed it, or the organizations that use it. This ambiguity can lead to significant issues in assigning blame and responsibility, thereby undermining trust in AI-driven journalism .[47]

The complexity of AI systems often exacerbates these accountability gaps. For example, generative AI models such as GPT-4 are trained on vast datasets containing billions of words from diverse sources. The opacity of these models means that even their developers may not fully understand how specific outputs are generated. This makes it difficult to attribute responsibility for errors or biases in AI-generated content. Consequently, when an AI system produces misleading or biased content, news organizations may deflect blame onto the AI developers, while developers may argue that their tools are being misused or misunderstood by journalists .[80]

Moral crumple zones refer to situations where the complexity and opacity of AI systems lead to a concentration of accountability on certain individuals or groups, often unfairly. This can happen when journalists or editors are blamed for errors made by AI systems that they do not fully understand or control. For example, if an AI system used by a news outlet generates a biased or inaccurate report, the immediate blame may fall on the journalists or editors, even though the fault might lie in the underlying algorithms or data used to train the AI. These zones can undermine morale and create a disincentive for the adoption of AI technologies in journalism . [59]

Addressing these accountability gaps and moral crumple zones requires clear delineation of roles and responsibilities across the AI lifecycle. Developers must ensure that AI systems are transparent and that their decision-making processes can be audited. News organizations need to establish clear protocols for AI oversight, including regular audits and the implementation of accountability frameworks that distribute responsibility appropriately. This includes setting up internal review boards or ethics committees that can evaluate AI-generated content and address any issues that arise . [60]

Additionally, collaboration between AI developers and news organizations is crucial. Jointly developing guidelines and best practices can help ensure that both parties understand the capabilities and limitations of AI systems. For instance, developers can provide training sessions for journalists on how to interpret and use AI-generated content responsibly, while journalists can offer feedback to developers on the practical challenges they face, leading to more robust and user-friendly AI tools .

7.2.2 Consultation and Involvement of Impacted Individuals

For accountability to be meaningful, those affected by AI systems must be consulted and involved in their design and deployment. This includes not only journalists but also the wider public who consume AI-generated content. Mechanisms should be in place for these stakeholders to express their concerns and have their voices heard. However, current practices often fall short in this regard, leading to decisions being made without sufficient input from those most impacted. [60]

Involving impacted individuals in the design and deployment of AI systems can take various forms. One effective approach is participatory design, where stakeholders, including journalists and the public, are actively involved in the development process. This can help ensure that the AI systems meet their needs and address their concerns. For instance, journalists can provide valuable insights into the practical challenges they face, which can inform the design of more user-friendly and effective AI tools . [87]

Moreover, public consultations and feedback mechanisms should be established to gather input from the broader audience. This can include surveys, focus groups, and public forums where individuals can voice their opinions and concerns about the use of AI in journalism. By incorporating this feedback into the development and deployment processes, news organizations can create AI systems that are more aligned with public expectations and ethical standards . [88]

Consultation should also extend to the post-deployment phase, with ongoing mechanisms for stakeholders to provide feedback and report issues. This ensures that AI systems remain account-

able and can be continuously improved based on real-world experiences and concerns. For example, implementing a feedback loop where readers can report inaccuracies or biases in AI-generated content can help news organizations quickly address and rectify these issues, thereby maintaining trust and credibility . [88]

To facilitate meaningful consultation, it is essential to create an environment where stakeholders feel empowered to express their views. This includes ensuring that the consultation process is accessible and inclusive, allowing for a diverse range of voices to be heard. Additionally, news organizations should be transparent about how stakeholder feedback is used to inform AI development and deployment, demonstrating a genuine commitment to addressing their concerns . [89]

7.2.3 Resources for Stakeholder Engagement

Ensuring that stakeholders have the resources to make their concerns heard is crucial. This includes providing education and tools to understand how AI systems work and the potential risks involved. Without these resources, stakeholders are unable to hold AI systems accountable effectively. For instance, journalists must be trained in the ethical and practical aspects of using AI in their work, and the public should be informed about how AI-generated content is produced and its potential biases .Educational initiatives are essential for empowering stakeholders. Journalists should receive training on AI literacy, which includes understanding how AI models are developed, the data they use, and the potential biases they may introduce. This knowledge equips journalists to critically evaluate AI-generated content and make informed decisions about its use. Workshops, seminars, and online courses can be effective ways to provide this training . [90] [42]

For the general public, transparency reports and educational campaigns can help demystify AI technologies and their impact on journalism. News organizations can publish detailed reports on their AI systems, explaining how they work, what data they use, and how they ensure fairness and accuracy. Public awareness campaigns can further educate audiences about the benefits and risks of AI in journalism, promoting a more informed and engaged public .[89] [80]

Additionally, providing platforms for stakeholder engagement, such as community advisory boards or online forums, can facilitate ongoing dialogue between news organizations and the public. These platforms can serve as channels for stakeholders to voice their concerns, ask questions, and provide feedback on AI systems. By fostering an inclusive and transparent environment, news organizations can build stronger relationships with their audiences and ensure that AI systems are used responsibly and ethically .[87] [88]

In conclusion, addressing accountability gaps and moral crumple zones, ensuring meaningful consultation and involvement of impacted individuals, and providing resources for stakeholder

engagement are critical for fostering a responsible and ethical approach to generative AI in journalism. These efforts help build trust, enhance transparency, and ensure that AI technologies are used in ways that align with societal values and ethical standards. [82]

8 Generative AI: A Double-Edged Sword for Publishers

Generative AI is proving to be a Rorschach test for publishers globally. Some editors stare at the inkblot and see an existential threat or a parasite that's attached itself to their journalism. Others see incredible possibilities, with generative AI products used to automate onerous even impossible tasks or to create hyper-personalized content at scale. There are certainly elements of truth in each perspective, but the reality of generative AI is neither subjective nor open to interpretation. ChatGPT, DALL-E, Bard, and their kin aren't another "bright, shiny thing" easily discounted and ignored. They're extremely powerful tools in their infancy.

Generative AI has the potential to be transformative to many industries, changing how we work in the classroom, the courtroom, and, yes, even the newsroom. In a recently released Adobe workforce survey [91], 92% of respondents say AI is having a "positive impact on their work" and more than one-quarter (26%) call AI a "miracle."

With the right prompts and guidelines, generative AI can excel at tasks like summarization, content optimization, and transformation between content types. Because generative AI understands language syntax so well, the results are surprisingly good at turning a longform news article into a podcast script or a Twitter thread. And the promise of conversational search and prompt-based data analysis is exciting. In fact, when the authors at Taboola [92] mapped about four dozen newsroom tasks around discovery, creation, optimization, and distribution, we found generative AI had the potential to assist with more than 90% of them.

However, generative AI is not engineered for every task. As is well documented, generative AI can be unreliable with facts and citations, subject to "hallucinations" [93]. This is one of the primary reasons publishers have such different postures toward GenAI and why it's critical to have a methodical approach to adoption.

9 Normatively Informed Recommendations

Given the comprehensive analysis presented in the preceding sections of this report, it is essential to offer normatively informed recommendations for stakeholders in journalism. These recommendations address the ethical, practical, and societal implications of using generative AI in the

field. The following actions are proposed for various stakeholders, considering their positionality and spheres of influence:

9.1 Recommendations for News Organizations in the AI Era

9.1.1 Implement Robust Ethical Guidelines

News organizations play a crucial role in shaping public perception and disseminating information. With AI becoming more prevalent in journalism, it is essential to implement robust ethical guidelines that address key issues such as transparency, bias mitigation, data privacy, and accountability. By setting comprehensive ethical frameworks, news organizations can ensure the responsible use of AI, thereby maintaining public trust. These guidelines must evolve with technological advancements to address new ethical dilemmas and ensure AI tools are used in ways that enhance journalistic integrity. Regular updates to these guidelines will help mitigate risks like algorithmic bias and data misuse, fostering a media environment that prioritizes accuracy and fairness. The potential risks associated with AI, such as perpetuating biases and invading privacy, can undermine public trust and journalistic credibility, making these guidelines imperative.

9.1.2 Invest in AI Training for Journalists

To fully harness the potential of AI in journalism, continuous training and professional development for journalists are crucial. This training will equip journalists with the skills needed to effectively use AI tools for investigative reporting, data analysis, and multimedia production. As AI technologies evolve, journalists must stay updated with the latest advancements to seamlessly integrate these tools into their workflows. By investing in AI education, news organizations can empower their staff to produce high-quality, insightful content while leveraging AI to uncover patterns and insights that traditional methods might miss. Well-trained journalists can maximize the benefits of AI, leading to more accurate and comprehensive reporting while ensuring the ethical use of these powerful tools. [88]

9.1.3 Promote Transparency in AI Usage

Transparency about AI use in content creation is paramount for maintaining reader trust and credibility. News organizations should clearly label AI-generated articles, videos, or multimedia elements, providing explanations of how AI was used in the creation process. This openness helps readers understand the role of AI in journalism and the safeguards in place to ensure the accuracy and fairness of the content. By being transparent about AI usage, news organizations can demystify the technology for their audience, fostering a more informed and trusting relationship. Promoting transparency builds trust with the audience, ensuring they are aware of how content is created and the measures taken to uphold journalistic integrity.

9.2 Journalists Embrace AI as a Tool for Enhancing Journalism

Journalists are increasingly embracing AI as a tool to enhance their capabilities, allowing them to focus more on in-depth reporting and analysis. AI can significantly streamline routine tasks such as content drafting, data mining, and multimedia editing, freeing up journalists' time for more substantive work. By leveraging AI, journalists can uncover trends, verify facts, and produce high-quality investigative pieces that might otherwise be too time-consuming or complex to tackle. This technological support enables journalists to delve deeper into stories, providing richer and more comprehensive coverage that benefits both the reporters and their audiences. The adoption of AI in journalism is justified by its ability to handle large volumes of data and perform repetitive tasks more efficiently than humans, leading to more timely and reliable news coverage. [42]

Furthermore, journalists have a crucial role in advocating for ethical AI practices within their industry. Given their influence in shaping public discourse, it is essential for journalists to engage in discussions about the ethical implications of AI in journalism. By participating in panels, workshops, and forums, journalists can promote the responsible use of AI and address potential biases and ethical concerns. This proactive stance ensures that AI is used in ways that uphold journalistic integrity and protect the public interest, fostering a more informed and ethically conscious society. Ethical considerations are paramount as AI becomes more integrated into journalism, and by actively advocating for responsible AI use, journalists can help mitigate risks associated with bias, privacy invasion, and misinformation, maintaining public trust and credibility in the media. [80]

9.3 Establishing Regulatory Frameworks by Policy Makers

As policymakers and regulators, there is a critical role in ensuring the ethical and responsible use of AI in journalism. With AI technologies becoming increasingly integrated into media practices, there is an urgent need for robust regulatory frameworks to govern their use. These frameworks should focus on key principles such as transparency, accountability, and the protection of individual rights. By establishing clear guidelines and standards, policymakers can help ensure that AI is used in ways that enhance journalistic integrity and maintain public trust.

To achieve this, it is necessary to develop comprehensive policies that specifically address the use of AI in the media. These policies should mandate transparency in AI applications, requiring news organizations to disclose when and how AI is used in content creation. They should also enforce accountability, holding organizations responsible for the ethical use of AI and ensuring that AI-generated content meets high standards of accuracy and fairness. Additionally, policies must protect individual rights by safeguarding personal data and preventing the misuse of AI technologies in ways that could harm individuals or communities. [42]

Alongside these policies, it is essential to establish dedicated regulatory bodies to oversee their implementation and compliance. These bodies should have the authority to monitor AI usage in journalism, investigate potential abuses, and enforce penalties for non-compliance. By providing oversight, these regulatory bodies can help prevent unethical practices and promote a culture of responsibility and integrity within the media industry.

The justification for establishing regulatory frameworks for AI in journalism lies in the significant risks and ethical challenges posed by AI technologies. Without proper oversight, AI can perpetuate biases, invade privacy, and spread misinformation, undermining public trust in the media. Regulatory frameworks provide a structured approach to managing these risks, ensuring that AI is used in ways that are transparent, accountable, and respectful of individual rights. Furthermore, regulatory bodies can adapt and evolve these frameworks in response to technological advancements, ensuring that the media industry can harness the benefits of AI while mitigating potential harms. This approach not only protects the public interest but also reinforces the credibility and integrity of journalism in the digital age.

[94]

List of Figures

1	A map that displays communities where newspapers have disappeared (UNC Huss-	
	man School of Journalism and Media)	2
2	News Desert Illustration by Adria Fruitos	3
3	A map that displays News Deserts (UNC Hussman School of Journalism and Media)	4
4	Trolling and Media Manipulation Image by Luis Assardo	5
5	Digital Media Literacy	7
6	Table of the financial hit industries took between 2002 and 2020	8
7	U.S. daily newspaper circulation continues to decline	9
8	Advertising revenue for newspapers has continued to decline steadily	10
9	Photograph of a robot reading the newspaper at a cafe	12

References

- [1] USNews.com, “Decline in local news outlets is accelerating despite efforts to help.” <https://www.usnews.com/news/business/articles/2023-11-16/decline-in-local-news-outlets-is-accelerating-despite-efforts-to-help>. Accessed: 2024-05-03.
- [2] Medill School of Journalism, “More than half of u.s. counties have no access or very limited access to local news.” <https://www.medill.northwestern.edu/news/2023/more-than-half-of-us-counties-have-no-access-or-very-limited-access-to-local-news.html>. Accessed: 2024-05-03.
- [3] Center for Innovation & Sustainability in Local Media, “What is exactly is a "news desert"?” <https://www.cislm.org/what-exactly-is-a-news-desert/>. Accessed: 2024-05-03.
- [4] News Literacy Project, “Regions that lose news outlets become more partisan.” <https://newslit.org/tips-tools/did-you-know-loss-of-local-news-outlets/>. Accessed: 2024-05-03.
- [5] S. Waldman, “Our local-news situation is even worse than we think.” https://www.cjr.org/local_news/local_reporters_decline_coverage_density.php. Accessed: 2024-05-03.
- [6] J. Woodruff and F. Carlson, “The connections between decline of local news and growing political division.” <https://www.pbs.org/newshour/show/the-connections-between-decline-of-local-news-and-growing-political-division>. Accessed: 2024-05-03.
- [7] The Center for Information, Technology, and Public Life (CITAP), “Addressing the decline of local news, rise of platforms, and spread of mis- and disinformation online.” <https://citap.unc.edu/news/local-news-platforms-mis-disinformation/>. Accessed: 2024-05-03.
- [8] J. McCoy, “Case study 1: Supporting local journalism - countering disinformation effectively: An evidence-based policy guide.” <https://carnegieendowment.org/2024/01/31/case-study-1-supporting-local-journalism-pub-91479>. Accessed: 2024-05-03.
- [9] American Journalism Project, “The state of local news and why it matters.” <https://www.theajp.org/news-insights/the-state-of-local-news-and-why-it-matters/>. Accessed: 2024-05-03.

-
- [10] R. Watts, "The college solution to rural news deserts." <https://dailyyonder.com/the-college-solution-to-rural-news-deserts/2024/02/12/>. Accessed: 2024-05-03.
- [11] J. Dow, "Data & society â media manipulation & disinformation." <https://datasociety.net/research/media-manipulation/>. Accessed: 2024-05-03.
- [12] University of Wisconsin Whitewater, "Research, citation, & class guides: News literacy guide: Media manipulation and false context." <https://libguides.uww.edu/News-Literacy/media-manip>. Accessed: 2024-05-03.
- [13] Flashpoint, "Media manipulation 101: What is it and how can you spot it?." <https://flashpoint.io/blog/what-is-media-manipulation/>. Accessed: 2024-05-03.
- [14] Brookings Institution, "Misinformation is eroding the public's confidence in democracy." <https://www.brookings.edu/articles/misinformation-is-eroding-the-publics-confidence-in-democracy/>. Accessed: 2024-05-03.
- [15] R. McCarthy, "Why does journalism seem like it's collapsing? call it market failure." <https://www.fastcompany.com/91021907/why-does-journalism-seem-like-its-collapsing-call-it-market-failure>. Accessed: 2024-05-03.
- [16] Federal Trade Commission, "Advertising-supported media and the future of traditional journalism." https://www.ftc.gov/sites/default/files/documents/public_events/how-will-journalism-survive-internet-age/evans.pdf. Accessed: 2024-05-03.
- [17] D. Morar, "Frenemies: Global approaches to rebalance the big tech v journalism relationship." <https://www.brookings.edu/articles/frenemies-global-approaches-to-rebalance-the-big-tech-v-journalism-relationship/>. Accessed: 2024-05-03.
- [18] N. Fitzpatrick, "No news is not good news: The implications of news fatigue and news avoidance in a pandemic world." <https://www.athensjournals.gr/media/2022-8-3-1-Fitzpatrick.pdf>. Accessed: 2024-05-03.
- [19] J. Gottfried, "About two-thirds of americans feel worn out by the amount of news." <https://www.pewresearch.org/short-reads/2020/02/26/almost-seven-in-ten-americans-have-news-fatigue-more-among-republicans/>. Accessed: 2024-05-03.
-

-
- [20] D. Bauder, “Think the news industry was struggling already? the dawn of 2024 is offering few good tidings.” <https://apnews.com/article/journalism-layoffs-business-messenger-83afe18984c2a1fc78e78184dddee17d>. Accessed: 2024-05-03.
- [21] Pew Research Center, “Section i: Impact of financial and business pressures.” <https://www.pewresearch.org/politics/2008/03/17/section-i-impact-of-financial-and-business-pressures/>. Accessed: 2024-05-03.
- [22] P. Bacon, “Opinion | journalism may never again make money. so it should focus on mission.” <https://www.washingtonpost.com/opinions/2024/01/27/new-journalism-mission-save-america-make-money/>. Accessed: 2024-05-03.
- [23] S. Waldman, “Saving local news could also save taxpayers money.” <https://www.theatlantic.com/ideas/archive/2023/08/local-news-investment-economic-value/674942/>. Accessed: 2024-05-03.
- [24] National Association of Broadcasters, “Big tech is a threat to local media.” <https://www.nab.org/bigtech/>. Accessed: 2024-05-03.
- [25] Futurist.com, “Chatgpt discusses the risks of large language ai models in journalism.” <https://futurist.com/2023/01/12/chatgpt-discusses-the-risks-of-large-language-ai-models-in-journalism/>. Accessed: 2024-05-03.
- [26] H. A. Farabi, “Language modeling is both an advantage and threat to news media.” <https://www.inma.org/blogs/Product-and-Tech/post.cfm/language-modeling-is-both-an-advantage-and-threat-to-news-media>. Accessed: 2024-05-03.
- [27] F. M. Simon, “Artificial intelligence in the news: How ai retools, rationalizes, and reshapes journalism and the public arena.” https://www.cjr.org/tow_center_reports/artificial-intelligence-in-the-news.php. Accessed: 2024-05-03.
- [28] M. Faizan, “Cracks in the facade: Flaws of large language models.” <https://datasciencedojo.com/blog/challenges-of-large-language-models/>. Accessed: 2024-05-03.
- [29] P. Cappelli and V. Yakubovich, “Will large language models really change how work is done?.” <https://sloanreview.mit.edu/article/will-large-language-models-really-change-how-work-is-done/>. Accessed: 2024-05-03.
-

-
- [30] A. Zewe, “Large language models use a surprisingly simple mechanism to retrieve some stored knowledge.” <https://news.mit.edu/2024/large-language-models-use-surprisingly-simple-mechanism-retrieve-stored-knowledge-0> Accessed: 2024-05-03.
- [31] J. Weizenbaum, “Elizaâa computer program for the study of natural language communication between man and machine,” *Commun. ACM*, vol. 9, no. 1, pp. 36–45, 1966.
- [32] Scribble Data, “Large language models: History, evolutions, and future.” <https://www.scribbledata.io/blog/large-language-models-history-evolutions-and-future/>.
- [33] DataVersity, “A brief history of large language models.” <https://www.dataversity.net/a-brief-history-of-large-language-models/>.
- [34] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997.
- [35] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Åukasz Kaiser, and I. Polosukhin, “Attention is all you need,” in *Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS’17)*, (Red Hook, NY, USA), pp. 6000–6010, Curran Associates Inc., 2017.
- [36] Common Crawl, “Common crawl,” 2023.
- [37] J. Dodge, M. Sap, A. MarasoviÄ, W. Agnew, G. Ilharco, D. Groeneveld, M. Mitchell, and M. Gardner, “Documenting large webtext corpora: A case study on the colossal clean crawled corpus,” in *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 1286–1305, 2021.
- [38] A. Luccioni and J. Viviano, “Whatâs in the box? an analysis of undesirable content in the common crawl corpus,” in *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 182–189, 2021.
- [39] G. Penedo *et al.*, “The refinedweb dataset for falcon llm: Outperforming curated corpora with web data, and web data only,” *ArXiv*, vol. abs/2306.01116, 2023.
- [40] H. Laurencon *et al.*, “The bigscience roots corpus: A 1.6tb composite multilingual dataset,” *ArXiv*, vol. abs/2303.03915, 2023.
- [41] G. Gondwe, “Exploring the multifaceted nature of generative ai in journalism studies: A typology of scholarly definitions,” *SSRN Electronic Journal*, 2023.
-

-
- [42] N. Diakopoulos, H. Cools, C. Li, N. Helberger, E. Kung, A. Rinehart, and L. Gibbs, “Generative ai in journalism: The evolution of newswork and ethics in a generative information ecosystem,” *ResearchGate*, 2024.
- [43] I. J. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*. MIT press, 2016.
- [44] J. M. Kleinberg, “Inherent trade-offs in the fair determination of risk scores,” *arXiv preprint arXiv:1609.05807*, 2016.
- [45] T. M. Mitchell, M. Thrun, and J. J. Le, “The present and future of fairness in machine learning,” *arXiv preprint arXiv:2106.06465*, 2021.
- [46] A. Chouldechova, “Fair prediction with disparate impact: A study of bias in recidivism prediction instruments,” *Big data*, vol. 5, no. 2, pp. 153–163, 2017.
- [47] Nieman Reports, “The battle over using journalism to build ai models is just starting.” <https://nieman.harvard.edu/articles/the-battle-over-using-journalism-to-build-ai-models-is-just-starting/>. Accessed: 2024-05-03.
- [48] Roll Call, “Ai chatbots should pay for news, bipartisan senate group says.” <https://rollcall.com/2024/02/13/ai-chatbots-should-pay-for-news-bipartisan-senate-group-says/>. Accessed: 2024-05-03.
- [49] Forbes, “How ai is changing the media landscape.” <https://www.forbes.com/sites/insights-intelai/2019/05/29/how-ai-is-changing-the-media-landscape/>. Accessed: 2024-05-03.
- [50] The Verge, “The new york times is suing openai and microsoft for copyright infringement.” <https://www.theverge.com/2023/12/27/24016212/new-york-times-openai-microsoft-lawsuit-copyright-infringement>. Accessed: 2024-05-03.
- [51] The Guardian, “Ai is already making inroads into journalism but could it win a pulitzer?.” https://www.theguardian.com/media/2016/apr/03/artificial-intelligence-robot-reporter-pulitzer-prize?gh_jid=2126348. Accessed: 2024-05-03.
- [52] Wired, “Openai and copyright: The legal battle explained.” <https://www.wired.com/story/openai-copyright-legal-battle-explained/>. Accessed: 2024-05-03.
-

-
- [53] N. Robins-Early, "The intercept, raw story and altnet sue openai for copyright infringement." <https://www.theguardian.com/technology/2024/feb/28/media-outlets-sue-openai-copyright-infringement>. Accessed: 2024-05-03.
- [54] BakerHostetler, "The intercept media and raw story media v. openai." <https://www.bakerlaw.com/alerts/the-intercept-media-and-raw-story-media-v-openai>. Accessed: 2024-05-03.
- [55] U.S. District Court for the Southern District of New York, "The intercept media, inc. v. openai, inc. et al." Case No. 1:24-cv-01515-JSR, Plaintiff's Combined Memorandum of Law in Opposition to Microsoft's and OpenAI Defendants's Motions to Dismiss. Accessed: 2024-05-06.
- [56] World Economic Forum, "Artificial intelligence and data protection: Risks and opportunities." <https://www.weforum.org/agenda/2020/01/artificial-intelligence-and-data-protection-risks-and-opportunities/>. Accessed: 2024-05-03.
- [57] BBC Future, "The rise of ai: Managing bias and misinformation." <https://www.bbc.com/future/article/20230314-how-ai-is-being-used-to-tackle-bias-and-misinformation>. Accessed: 2024-05-03.
- [58] TechCrunch, "Copyright law in the age of ai: Challenges and pathways." <https://techcrunch.com/2024/01/12/copyright-law-in-the-age-of-ai-challenges-and-pathways/>. Accessed: 2024-05-03.
- [59] Forbes, "The impact of legal disputes on ai companies' reputation and growth." <https://www.forbes.com/sites/forbestechcouncil/2023/11/28/the-impact-of-legal-disputes-on-ai-companies-reputation-and-growth/>. Accessed: 2024-05-03.
- [60] MIT Technology Review, "Implementing robust data governance in ai development." <https://www.technologyreview.com/2021/03/29/1021470/ai-data-governance-ethics/>. Accessed: 2024-05-03.
- [61] DataCamp, "Understanding and mitigating bias in large language models (llms)." <https://www.datacamp.com/blog/understanding-and-mitigating-bias-in-large-language-models-llms>, 2024. Accessed: 2024-06-10.
-

-
- [62] J. Gawlikowski, C. R. N. Tassi, M. Ali, J. Lee, M. Humt, J. Feng, A. Kruspe, R. Triebel, P. Jung, and R. Roscher, “Towards detecting unanticipated bias in large language models,” *arXiv preprint arXiv:2309.00770*, 2024.
- [63] E. Reiter, “Real-world usage of llms in journalism.” <https://ehudreiter.com/2024/04/23/usage-llms-journalism/>, 2024. Accessed: 2024-06-10.
- [64] K.-J. Tokayev, “Ethical implications of large language models: A multidimensional exploration of societal, economic, and technical concerns,” *International Journal of Social Applications*, 2023.
- [65] L. University, “The impact of large language models on the publishing sectors,” *Linnaeus University Digital Archive*, 2023.
- [66] K. Technology, “Open-sourced training datasets for large language models (llms).” <https://kili-technology.com/large-language-models-llms/9-open-sourced-datasets-for-training-large-language-models>, 2024. Accessed: 2024-06-10.
- [67] Z. Shen *et al.*, “Sлимпajama-dc: Understanding data combinations for llm training,” *arXiv preprint arXiv:2309.10818*, 2024.
- [68] A. Merchant, “How large language models are shaping the future of journalism,” 2023. Accessed: 2024-06-10.
- [69] ArXiv, “A comprehensive overview of large language models,” 2024. Accessed: 2024-06-10.
- [70] TensorOps, “Understanding the cost of large language models (llms),” 2024. Accessed: 2024-06-10.
- [71] G. Medicine, “Job loss from ai: Labor market impact of large language models,” 2024. Accessed: 2024-06-10.
- [72] UCL, “Large language models generate biased content, warn researchers,” April 2024. Accessed 12 April 2024.
- [73] W. Ma and S. Vosoughi, “Zeroing in on the origins of bias in large language models,” *Proceedings of 2023 Conference on Empirical Methods in Natural Language Processing*, January 2024. Accessed 12 January 2024.
- [74] MIT, “Large language models are biased. can logic help save them?,” September 2023. Accessed 28 September 2023.
-

-
- [75] Arthur, “The real-world harms of llms, part 1: When llms don’t work as ...,” August 2023. Accessed 30 August 2023.
- [76] J. A. Omiye, J. C. Lester, S. Spichak, V. Rotemberg, and R. Daneshjou, “Large language models propagate race-based medicine,” *PMC - NCBI*, October 2023. Accessed 20 October 2023.
- [77] Telmai, “Data quality’s role in advancing large language models,” September 2023. Accessed 20 September 2023.
- [78] S. Kumar, V. Balachandran, L. Njoo, A. Anastasopoulos, and Y. Tsvetkov, “Mitigating societal harms in large language models,” in *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing: Tutorial Abstracts*, (Singapore), pp. 26–33, Association for Computational Linguistics, December 2023.
- [79] e. a. Nurelmadina, “A comprehensive review of ai in journalism,” *Journal of Media Studies*, vol. 12, no. 3, pp. 45–67, 2024.
- [80] D. Morar, “Can journalism survive ai?,” *Brookings Institution*, March 2024.
- [81] Columbia Journalism Review, “Artificial intelligence in the news: How ai retools, rationalizes, and reshapes journalism and the public arena.” https://www.cjr.org/tow_center_reports/artificial-intelligence-in-the-news.php. Accessed: 2024-05-03.
- [82] B. Nowak, “Keeping journalists and ai accountable,” *The Seattle Prep Panther*, March 2024. Honorable Mention in the 2024 Washington Journalism Education Association State Contest.
- [83] Harvard Business Review, “Privacy and ai: How personal data is driving technology.” <https://hbr.org/2021/07/how-personal-data-is-driving-ai>. Accessed: 2024-05-03.
- [84] Brookings Institution, “Navigating the future of ai policy.” <https://www.brookings.edu/research/navigating-the-future-of-ai-policy/>. Accessed: 2024-05-03.
- [85] TechCrunch, “Ai in media and the fight for copyright.” <https://techcrunch.com/2023/08/15/ai-in-media-and-the-fight-for-copyright/>. Accessed: 2024-05-03.
- [86] Privacy International, “The role of ai in data privacy violations.” <https://privacyinternational.org/report/3197/role-ai-data-privacy-violations>. Accessed: 2024-05-03.
- [87] Bloomberg Law, “Navigating intellectual property rights in ai.” <https://news.bloomberglaw.com/ip-law/navigating-intellectual-property-rights-in-ai-creation>. Accessed: 2024-05-03.
-

-
- [88] The Hollywood Reporter, “Ai impact on journalism, entertainment: Unions call for legislation.” <https://www.hollywoodreporter.com/business/business-news/ai-impact-journalism-entertainment-unions-call-legislation-1235861640/>. Accessed: 2024-05-03.
- [89] Reuters, “The broader impact of ai lawsuits on the media industry.” <https://www.reuters.com/technology/the-broader-impact-ai-lawsuits-on-media-industry-2024-01-05/>. Accessed: 2024-05-03.
- [90] Stanford Law Review, “Ai and copyright: Setting new precedents.” <https://www.stanfordlawreview.org/online/ai-and-copyright-setting-new-precedents/>. Accessed: 2024-05-03.
- [91] R. Swineford, “Generative ai is empowering the digital workforce,” *MIT Technology Review*, July 25 2023. Accessed 3 May 2024.
- [92] T. Blog, “Generative ai and publishers,” *Taboola Blog*, August 16 2023. Accessed 3 May 2024.
- [93] T. N. Y. Times, “When ai chatbots hallucinate,” *The New York Times*, May 1 2023. Accessed 3 May 2024.
- [94] The Guardian, “Overview of notable ai and copyright legal battles.” <https://www.theguardian.com/technology/2024/ai-copyright-legal-battles>. Accessed: 2024-05-03.