Highlighting A Gap in Journalism's Environmental Discourse on the Integration of Artificial Intelligence

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Abstract

As artificial intelligence (AI) becomes increasingly integrated into the field of journalism, there is a pressing need to address its environmental implications, a facet often overlooked in discussions shaping the industry's trajectory. This paper provides a foundational overview of AI's complex environmental impacts by examining existing literature and emerging trends. It underscores the challenges stemming from AI's rapid adoption while emphasizing journalism's pivotal role in influencing a push towards sustainability. Furthermore, the paper emphasizes the important role journalism plays in fostering public awareness of AI's environmental implications and highlighting the need for the adoption of interdisciplinary sustainable practices. Finally, the paper discusses potential strategies for mitigating AI's environmental impact, including the development of standardized reporting systems and the prioritization of renewable energy sources in AI operations. By fostering collaborative efforts between the public, researchers, and industry stakeholders, the journalism community can contribute significantly to shaping a more sustainable future for AI-driven journalism and beyond.

Introduction

The integration of artificial intelligence into the field of journalism has heralded a new era of innovation within the industry, offering a litany of promising advancements. Key figures have championed the increased adoption of AI across both large and small publications, driving the swift uptake of these innovative technologies alongside continued investments into research and development (Beckett; Amponsah and Atianashie; Simon and Isaza-Ibara). However, amidst the ongoing discourse surrounding AI's impact on journalism, the environmental sustainability of the movement has been largely overlooked and threatens to negatively impact the future of the field. Journalists are urged to use the presented arguments to reflect on both their utilization and reporting of AI.

Despite the exciting prospects AI brings to journalism, the environmental impact remains a critical consideration. While academic and journalistic perspectives on the overall impact of AI in journalism may differ (Miroshnichenko; Broussard et al), the environmental strain resulting from its rapid development and implementation consistently goes unacknowledged. This paper underscores the need for the journalism community to broaden their perspective and consider the vast external implications of their actions, advocating for a solution-oriented approach. To provide a foundational overview, this paper explores AI's widespread integration into newsrooms, discusses existing ethical discourse among journalists, conducts a comprehensive analysis of the technology's environmental impact, and proposes potential solutions for the future. The goal is to raise awareness, educate the journalism community, and prompt thoughtful consideration of the environmental repercussions of the rapid adoption of AI, fostering a more sustainable approach to its integration.

Section 1: Navigating AI's Integration in Newsrooms

Historically, the advent of new and innovative technology has heavily influenced the field of journalism (Nord; Scott). The emergence of technologies such as the printing press and the internet compelled many journalists to adapt and find innovative ways to deliver their services while upholding their moral and ethical values, and the arrival of AI has had a similar impact.

Artificial intelligence is an umbrella term that encompasses the development of computer systems that are capable of performing tasks traditionally within the purview of human cognition. Examples of these tasks include learning from experience, understanding natural language, recognizing patterns, solving problems, and adapting to new situations (Anderson 140). The technology's capability to autonomously execute complex cognitive functions through replicating or simulating human intelligence, has facilitated its continuous evolution through research and development and widespread integration across various fields, including journalism.

Despite ongoing efforts, quantifying the precise extent of said integration remains challenging. Nonetheless, contemporary research indicates a substantial and escalating presence of AI across multiple dimensions of journalism (Simon, 13). In the ever-accelerating landscape of technological innovation, the significance of staying attuned to developments in the world of AI cannot be overstated. Our ability to anticipate, adapt, and responsibly leverage its capabilities could potentially have the power to shape the trajectory of our collective future.

The following sections will demonstrate how the journalism industry has been gradually incorporating AI-powered technology into its workflows for more than a decade. Francesco Marconi, author of *Newsmakers: Artificial Intelligence and the Future of Journalism*, categorized the recent shift towards AI in journalism into three waves: automation, augmentation, and generation. While these waves are conceptual and represent a continuum

rather than distinct phases of the evolution of AI, they provide a well-structured framework for understanding the expansion of AI in the newsroom (Marconi 60).

The Automation Wave

The early adoption of AI in newsrooms was a deliberate and strategic endeavor aimed at marrying industry demands with the transformative promises embedded within AI technologies. To stay competitive in an evolving media landscape, it became imperative for news organizations to optimize the operational and financial facets of their business (van Dalen 649). Relying on relatively simple, rule-based computational processes, natural language generation (NLG) quickly became a popular tool within select newsrooms as it allowed journalists to automate data-driven news stories, converting structured data, organized in a well-defined and highly predictable manner, into digestible written narratives (Reinhart and Kung 11). Capable of producing large quantities of content for low additional costs, NLG was initially leveraged to automate routine stories such as financial reports, sports results, and economic indicators, ultimately providing journalists with more time to focus on more labor-intensive tasks such as investigative journalism.

One of the earliest examples of this phenomenon came when Northwestern University's Intelligent Information Laboratory designed a program called StatsMonkey, that was programmed to process statistics from baseball games and produce computer-generated news stories based on the provided information (Flueckiger 9; Shapiro et al). As NLG technology developed, it became more accessible to interested parties, such as large news organizations, which began to implement these systems in their newsrooms.

In 2014, the Associated Press became one of the first major early adopters of AI in journalism when they partnered with software company Automated Insights to implement their

NLG-powered platform, Wordsmith, into their newsroom. The tool was used to produce automated earnings reports, which freed up an estimated 20% of their journalist's time, allowing them to engage in "more complex and qualitative work" (Marconi et al 4). As a result, AP was able to provide customers with 12x the corporate earnings reports, increasing their production from 300 reports a quarter to over 3700, which subsequently included a substantial amount of very small companies that previously failed to receive much attention (Marconi et al 4; Peiser).

This significant increase in production represents the computational power and allure of AI in the newsroom. As journalists were faced with the exponential growth of information due to the rise of the internet, pursuing worthwhile yet labor intensive stories became much more difficult, due to a lack of time and resources (Latar 65). AI-powered tools were initially seen as a potential aid to this issue. The Canadian news market appeared to be slower to adopt this technology, with news outlets like the Canadian Press and the Toronto Star implementing programs akin to StatsMonkey and Wordsmith in 2017, to automate stories covering local hockey leagues like the CHL and OHL (Consky). By leveraging these programs journalists became able to relinquish certain aspects of their day-to-day workloads to increasingly intelligent machines. More and more news organizations began to realize the beneficial qualities of AI and searched for ways to use these technologies to their advantage to lessen their staff's workload while simultaneously bolstering their profit margins (Lecompte; Gani and Haddou).

This modernization marked the dawn of a new era in journalism, which saw intelligent machines slowly carve out a foothold in newsrooms around the world. However, while these novel tools allowed some journalists to re-allocate their time towards more labor intensive tasks, the rapid spread of the technology was met with speculation from the greater journalism community.

Ethical Concerns of the Automation Wave

During the initial stages of the automation wave, “automation anxiety” ran rampant, as many feared that the introduction of artificial intelligence would have irreversible adverse effects (Askt; van Dalen 649). Job security became a primary concern as AI-powered tools increasingly automated routine stories, displacing the work of trained journalists and raising concerns about the expendability of various roles in the newsroom. Despite the scarcity of documented cases of journalists losing their jobs to AI at this time, concerns about job displacement persisted. These concerns were partly fueled by predictions from interdisciplinary experts about the future of the industry. For example, in 2012, Professor Krisitian Hammond, co-founder of Narrative Science, forecasted that "in 15 years, 90 percent of news will be written by algorithms" (Rosen). This prediction reflected a prevailing sentiment that intelligent machines would swiftly dominate news production. Despite arguments asserting AI's inability to replicate the emotional intelligence, critical thinking, and the creativity innate to human journalists (Diakopoulos 12), apprehensions about its disruptive potential persisted within the community. As industry leaders forged ahead with the integration of AI to bolster efficiency, productivity, and profitability, academics and journalists issued warnings about the potential long-term repercussions of their endeavors (Latar 67).

Amidst the ongoing “automation anxiety”, the proliferation of AI also sparked concerns regarding the erosion of trust between publications and their readership. A survey by the AI Initiative at the London School of Economics & Political Science revealed that over 60% of respondents harbored ethical apprehensions about AI's integration into journalism, citing editorial quality as a primary concern (Sunny 17). During the nascent stages of AI’s integration in journalism (approx. 2009-2014), public skepticism surged as the lack of awareness about AI's

role in news production blurred the lines between human and AI-generated content. Without transparent disclosure from news outlets, distinguishing between human and AI-authored articles became challenging, fostering a climate of distrust (Clerwall 526; Carlson 427, Toff and Simon 2). Ethical debates surfaced regarding the necessity of disclosing AI involvement in article production to the public. While a growing number of publishers began responding to these concerns by adding labels to AI-generated content or by directly crediting AI programs in the by-line (i.e. the LA Times' Quakebot), there was no shared consensus about what such disclosure should look like nor agreement over what level of AI-involvement should trigger such labeling (Toff and Simon 2; Pantano). Additionally, questions surfaced regarding the allocation of blame in cases where AI made significant editorial errors, such as the incident involving the LA Times' Quakebot in 2017, when the bot erroneously reported an earthquake that occurred over 90 years prior (Cabral), prompting discussions about accountability and responsibility.

As AI technology continued to advance rapidly, these concerns and debates persisted, especially with AI becoming increasingly adept at producing content indistinguishable from human-authored writing. Amidst this evolution, questions persisted about the level of transparency surrounding AI's growing role in newsrooms. Despite these concerns, research and development of AI continued to forge ahead, fueled by large-scale investments from governments and corporations, propelling the AI revolution forward (Luccioni et al 50). The interdisciplinary benefits served as a potent catalyst for AI's trajectory, ultimately leading to the introduction of the augmentation wave of AI in journalism.

The Augmentation Wave

Fueled by the development and widespread adoption of machine learning (ML) and its subsequent branches, the augmentation wave swept across many news organizations,

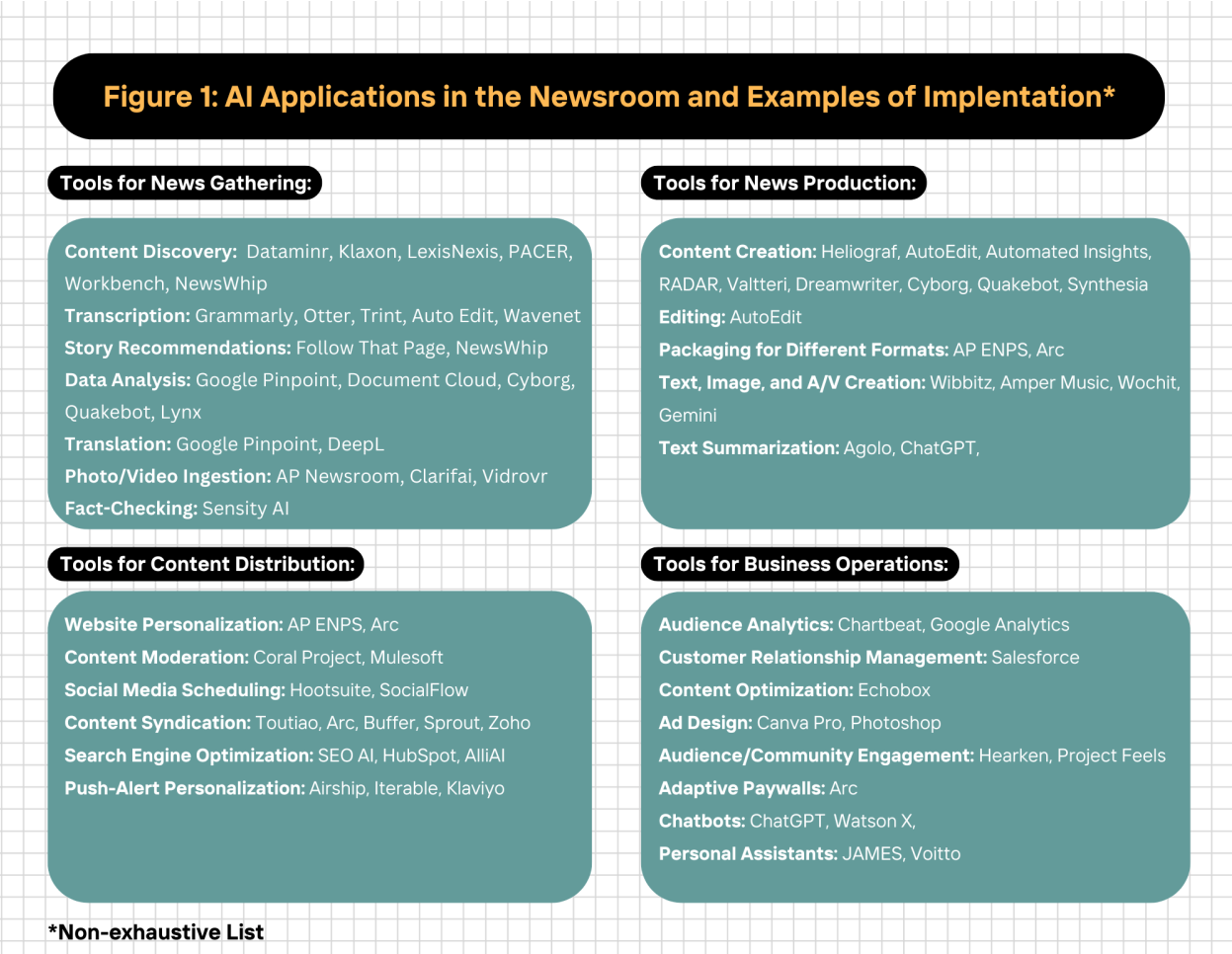
fundamentally reshaping journalism practices. Machine learning, a computationally intensive subset of AI, revolutionized the field by enabling algorithms to autonomously analyze, learn, and recognize patterns from large datasets through an elaborate training process (Blank 6; M. Hansen 8). Equipped with supervised, unsupervised, and reinforcement learning capabilities, ML systems exhibited the potential to make predictions, decisions, generate insights, and adapt their responses based on user input, both with and without task specific programming (Blank 23). This distinct venture from existing NLG technologies marked the beginning of an era where ML algorithms became pivotal in the augmentation of journalistic workflows as well as allowing news organizations to navigate an evolving media landscape.

Journalists, once burdened with labor-intensive processes, could now harness ML algorithms to augment their work across diverse domains. Key branches of ML, such as deep learning (DL), natural language processing (NLP), and computer vision (CV), became important technologies for optimizing various tasks. From speech transcription to social media monitoring, language translation, and data indexing, AI-driven solutions streamlined workflows, enabling some journalists to focus on more demanding tasks such as investigative reporting and narrative storytelling (Marconi 58).

A notable example of machine learning's augmentative power came from the International Consortium of Investigative Journalists' (ICIJ) 2016 Pulitzer Prize-winning investigation, *The Panama Papers.* Despite not utilizing artificial intelligence initially, over 350 reporters from 80 countries collaborated to analyze 2.6 terabytes of data (11.5 million documents), spanning four decades, revealing the extensive network of financial activities orchestrated by Mossack Fonseca, a Panama-based law firm. This investigation shed light on the secretive world of offshore finance, exposing the involvement of politicians, celebrities, and the

global elite in illicit activities (Fitzgibbon). While the investigation was resource-intensive and time-consuming, the eventual integration of AI accelerated the process significantly, as acknowledged by ICIJ's web applications developer, Matthew Caruana Galizia (Marconi et al 14). Leveraging open-source data mining technology, graph databases, and other AI-powered tools, the ICIJ's team efficiently organized, indexed, filtered, and searched through the extensive data trove, significantly enhancing their investigative capabilities. These technologies amplified the journalists' existing skills and aided in uncovering complex patterns and valuable insights from the vast dataset. While AI-powered tools can optimize the processing, organizing, and labeling of millions of documents, it requires an experienced journalist to make connections between related pieces of evidence and build an accurate and compelling narrative from them through investigation. Despite the overwhelming capabilities of AI technologies during the augmentation wave, they remained largely human-centered, in-so-far as they required an intelligent operator in order to produce any form of meaningful output (Simon 32).

In contrast with these developments, as ML technologies advanced, they not only empowered journalists with groundbreaking capabilities but also revolutionized automation, a trend that had already begun to reshape newsrooms during the preceding automation wave. Through the deployment of more powerful generative AI models, journalists found themselves equipped to swiftly craft essential content like headlines, summaries, and short articles, saving them invaluable time for tackling more complex endeavors (Marconi 2). Despite the need for meticulous editing and fact-checking, these innovations represented monumental strides towards achieving unparalleled efficiency in news production. For a more expansive list of AI applications in newsrooms, please refer to Figure 1.



AI's widespread integration became evident as numerous news organizations, including major publishers like the New York Times, Bloomberg, Reuters, the BBC, and the Washington Post, gradually embraced various forms of augmentative AI in their operations. The actions of these larger organizations prompted smaller market publications to recognize the value of AI and follow suit as the technology became more accessible, further contributing to its widespread adoption throughout the industry (Underwood; Reinhart and Kung 46). This shift pledged to improve efficiency and productivity while simultaneously elevating the quality and depth of journalistic content, enriching the news consumption experience for audiences worldwide. As AI technologies continued to evolve, their impact on journalism expanded beyond operational

enhancements, influencing audience engagement strategies, content personalization, and revenue models, thereby promising to reshape the entire landscape of modern journalism.

ML-powered analytic systems proved to augment audience engagement strategies by providing invaluable insights into audience behavior, preferences, and consumption patterns. By analyzing vast amounts of data, AI algorithms could identify trends, anticipate audience interests, and tailor content delivery to maximize engagement. This data-driven approach enabled news organizations to fine-tune their editorial strategies, optimize distribution channels, and foster stronger connections with their audiences (Simon et al 8; Jerbi 2; Gow et al). Additionally, AI played a pivotal role in content personalization, allowing news outlets to deliver highly relevant and targeted content to individual users. Through leveraging ML-powered algorithms, news organizations could analyze user demographics, past interactions, and real-time feedback to dynamically adjust content recommendations and presentation formats (Kreft et al 138; Oukka). This level of personalization not only promised to enhance the user experience but also increase retention rates and loyalty among their audiences. By delivering content that resonated with each user's preferences and interests, news organizations hoped to foster deeper engagement and build stronger relationships with their readership base.

AI-driven technologies have shown potential to revolutionize revenue models within the journalism industry. By harnessing the power of data analytics and predictive algorithms, news organizations can optimize subscription models, advertising strategies, and monetization efforts (Caswell). AI-enabled platforms are capable of identifying high-value subscribers, predicting churn rates, and segmenting audiences for targeted advertising campaigns. Additionally, AI-powered content recommendation engines can promote premium content to users most likely to convert, driving subscription revenues and reducing reliance on traditional advertising models

(Beckett 31; Simon 37). While the evolution of AI has proved to have a potentially transformative impact on journalism, reshaping its practices, strategies, and business models, critics remained skeptical, citing various ethical concerns and considerations that they felt accompanied the aforementioned augmentation wave of AI in journalism.

Ethical Concerns of the Augmentation Wave

The continued proliferation of artificial intelligence in the news industry sparked significant ethical concerns, echoing those raised during the preceding automation wave (i.e., job security, erosion of trust, etc.), while also introducing new challenges. For an extensive overview of these challenges, see (Smith et al; Becker et al; Toff and Simon). Some of the most common concerns that began to develop during the augmentation wave included algorithmic transparency, algorithmic bias, and data privacy. Many peer-reviewed articles were published addressing these concerns in an effort to educate stakeholders on the potential implications of the continued integration of AI in the newsroom (M Hansen et al; A Hansen et al; Amponsah and Atianashie; Broussard et al). However, it is important to address them here to provide a diverse scope of the existing ethical concerns surrounding this topic.

As a starting point, transparency and accountability pose significant challenges in the era of AI augmentation. The opacity of AI algorithms, often referred to as "black boxes," raise questions about how decisions are made and who is responsible for them. Without clear visibility into the inner workings of these algorithms, stakeholders struggle to hold AI systems accountable for their actions, raising concerns about fairness, trustworthiness, and ultimately, journalistic integrity (Broussard et al 684). While the onus of AI transparency lies with the developers of AI systems, the journalism community wields the tools, platforms, and expertise to apply the necessary pressure to hopefully enact change in the near future.

As a result of this lack of transparency, it becomes exceedingly challenging to identify and address deep-seated biases within algorithms. Machine learning algorithms, when trained on historical data, may inadvertently perpetuate existing biases present in the data, leading to the generation of biased or discriminatory content (Amponsah and Atianashie). High-profile examples include racial bias in risk assessment tools within the criminal justice system, gender discrimination in automated hiring, and the automated determination of eligibility for social assistance, all of which have raised alarms about the ethical implications of AI-driven decision-making processes **(**Angwin et al; Dastin**;** Eubanks 85**).** These biases are capable of influencing how news stories are framed, presented, and prioritized. Without transparency, it's difficult to detect and mitigate these biases, potentially leading to the propagation of misinformation or the reinforcement of harmful stereotypes.

Moreover, the collection and analysis of user data for personalized content recommendations raises profound questions about data privacy. While AI-driven personalization aims to enhance user experience, it also raises concerns about surveillance, data misuse, and the erosion of individual privacy rights (Sher and Benchlouch). Striking a delicate balance between personalization and privacy protection is paramount to ensuring responsible AI use in journalism and maintaining trust between news organizations and their audiences.

Navigating the ethical complexities of AI augmentation in journalism requires a multifaceted approach. This entails embracing transparent AI practices, implementing rigorous bias detection and mitigation strategies, establishing clear guidelines for safeguarding user data privacy, and fostering ongoing dialogue among stakeholders. By addressing these challenges proactively, the journalism industry can leverage AI's transformative capabilities while upholding ethical standards and preserving public trust in the media.

The Generation Wave

The generation wave of artificial intelligence epitomizes the pinnacle of AI integration into journalism thus far, introducing sophisticated large language models (LLMs) and advanced generative models like OpenAI's GPT-4 and DALL-E. These models consolidate elements of various branches of AI such as machine learning (ML), deep learning (DL), and natural language processing (NLP) to understand and generate language (text) and mixed media (images, videos, audio, etc) on a large scale (Simon et al 9). Unlike their predecessors, which primarily offered assistance and augmentation capabilities, these cutting-edge models redefined the role of AI in content creation and delivery within journalism.

LLMs and first-rate generative models demonstrate remarkable capabilities, including generating articles, reports, and multimedia content autonomously and with unprecedented accuracy**.** The growing popularity of these tools is exemplified by Open AI's ChatGPT (powered by GPT-4), which gained over 1 million users within a week of its public release in 2022 (Mollman)**,** and currently amasses over 100 million weekly users (Porter). With exponential improvements in computational power, modern AI technologies such as ML, DL, and NLP are capable of producing content that closely rivals human quality and, at times, becomes indistinguishable. The accessibility of open-source AI tools empowers both journalists and the public to create sophisticated content in various languages and styles, blurring the line between human and AI-generated content.

Some experts believe that the integration of generative AI in journalism has changed the narrative that the industry has historically been slow to adapt to new technologies (Simon). One scholar was quoted stating; "a decade of innovation projects, lessons from the growth of social media and hard-won operational experience in applying big data and machine learning to

recommendations, subscription management and investigative journalism have left the news industry better equipped to handle AI than many assume" (Caswell). Despite the growing concerns surrounding the rapid adoption of AI in journalism (which will be discussed in the following section), the industry is steadily moving towards a future heavily influenced by AI. Experts at the Associated Press forecast that 2024 will be a pivotal year, as smaller newsrooms, operating with fewer resources than their larger counterparts, seize the opportunity to leverage open-source AI tools, enhancing efficiency and reducing costs (Kung). An illustrative example of this trend is the Open Society Foundations' AI in Journalism Challenge (AIJC), which underscores the increasing interest in generative AI within the industry and offers a glimpse into its potential future. The global program selected 12 small "digital-first" newsrooms from a pool of 113 applicants to develop generative AI projects with the potential to revolutionize their journalism practices. Structured as a competition, participating teams received mentoring, educational resources, and financial support to develop their AI projects, which they presented to a judging panel of news industry experts. Following the selection of five finalists, a final round of demonstrations and judging took place at the Splice Beta journalism festival in Chiang Mai, Thailand, in November 2023. Rappler, an online news website based in the Philippines, won the competition after demonstrating their TL;DR project (too long; didn't read), receiving a $30,000 grant for their efforts (Caswell).

Such initiatives highlight the transformative potential of artificial intelligence in the journalism industry. As the technology continues to become more accessible, smaller news organizations are being incentivised to devise plans to incorporate existing AI-tools, and as this example shows, even create their own. The Associated Press has even launched a "Local News AI Training Course" aimed at helping local newsrooms identify and embrace AI-based solutions,

underscoring the growing enthusiasm among larger news organizations for AI's expanded accessibility within the journalism community (Associated Press). Additionally, given the open-source nature of certain models, individuals from all walks of life can now tap into the computational capabilities of LLMs and generative models to craft sophisticated written and visual content across various languages and styles, often indistinguishable from human creations. As awareness of these technologies' capabilities grow within the journalism community, it is likely that more efforts will be directed towards developing pragmatic, measurable, and transformative AI-powered technologies for journalistic purposes. However, amidst this progress, journalists and scholars remain vigilant in outlining the obstacles and challenges accompanying the widespread and rapid adoption of AI. This persistence in identifying potential issues has left some stakeholders apprehensive about the future trajectory of the field.

Ethical Concerns of the Generation Wave

As the generation wave has swept through the field of journalism, a host of new ethical concerns emerged alongside the amplification of existing ones. The evolution of artificial intelligence, enabling AI-powered tools to approach human-like intelligence, raised questions about the societal and professional implications of these advancements. Among the newly surfaced concerns like plagiarism, accuracy, and autonomy, the proliferation of deepfakes and misinformation took center stage, prompting a critical analysis of the industry's ongoing transformation (Vaccari et al 145). For example, in 2018, China’s state news agency, Xinhua, began experimenting with creating entirely AI-generated news anchors capable of 24/7 reporting (Xinhua; Loh). In contrast with the excitement and promise that was associated with this technological feat, many became apprehensive about the potential negative or malicious applications of this technology. While these capabilities can be harnessed for benign purposes

like daily news reporting, they also carry the risk of deception and the dissemination of harmful ideologies. For instance, researchers utilized widely available AI tools to synthesize an audio recording of CNN anchor Anderson Cooper reading a fictitious script, coupled with a modified video clip mimicking his expressions and mannerisms, thus creating a deep fake (Bohacek et al). Expanding upon this phenomenon, ML algorithms facilitated the creation of face-grafting technology that can seamlessly superimpose one person's expressions onto another's face with remarkable realism (Vaccari et al 139). The potential misuse of such technology poses threats to societal integrity, prompting apprehension within the journalism community regarding its implications.

In tandem with the rise of deep fakes, the generation wave ushered in heightened concerns regarding the dissemination of misinformation. Large language models equipped users with potent generative capabilities, enabling the production of content with the potential to sow discord and mislead the public. With the rapid expansion of the online media landscape, misinformation can propagate swiftly, evading detection and inflicting significant harm (Monteith et al 34). Unlike earlier methods of crafting and disseminating misinformation, AI-powered tools offer unprecedented scalability and accessibility, circumventing traditional safeguards (Akhtar et al 7). This unchecked dissemination challenges foundational journalistic ethics of truth, transparency, and accuracy, underscoring the urgent need for regulation and awareness within the industry.

This section has worked to provide an overview of the integration of AI into the news industry, and how these developments have sparked extensive debate, highlighting concerns ranging from job security to misinformation. Throughout the automation, augmentation, and generative waves, academics and journalists alike have swiftly highlighted the dual nature of AI

technologies: promising important advancements alongside significant threats to the core tenets of journalism. However, upon reviewing the existing literature focused on the structural implications of AI's adoption into journalism practices, a significant gap emerged. The environmental implications of the rapid proliferation of AI remain conspicuously absent from the journalism community's ethical discourse. Despite ample evidence demonstrating the environmental impacts of AI, the topic has seldom been discussed. For example, a recent report from Columbia University's TOW center on the adoption of AI in journalism fails to mention the environmental impacts of AI. Despite conducting an extensive review of the use of AI across the editorial, commercial, and technological domains of news organizations, as well as addressing the direct challenges associated with integrating AI into the newsroom, the report overlooks this crucial aspect (Simon 1).

As AI technologies continue to permeate newsrooms worldwide, it becomes imperative to address their environmental footprint alongside other ethical considerations. Awareness of these environmental ramifications is essential for informed decision-making and the development of sustainable AI practices in journalism and beyond. Given the likely inevitability of artificial intelligence's continued growth, it is imperative to engage in a comprehensive discussion of its implications for the industry. Journalists must consider how they will cover this issue in their own work, recognizing AI's pervasive influence and potential impact on various aspects of journalism. The subsequent sections of this paper delve into a comprehensive examination of the environmental ramifications of AI integration, emphasizing the indispensable role that the journalism community must assume in shaping a sustainable future.

Section 2: Overview of the Environmental Impact of AI

In 2019, Strubell et al published their seminal paper on the environmental impact of artificial intelligence, which sparked a wave of interest and research from the general AI community. Their work claimed that the process of training a single large natural language processing system was extremely harmful to the environment, generating an estimated 620,000 lbs of CO_2 equivalent (CO_2e), which equated to the lifetime emissions of approximately 5 average cars (Strubell et al 1). Despite these calculations later being deemed an overestimation by Patterson et al in 2021, the paper served its purpose, as it brought necessary attention to a previously underreported issue (Patterson et al 9). In response to Strubell et al's findings, a surge of research began to appear, investigating the environmental impact of artificial intelligence. Verdecchia et al's 2023 study, *A Systematic Review of Green AI,* provided an overview of the existing research pertaining to the carbon footprint of AI, identifying a significant growth in the discussion from 2020 onward, with 76% of the papers being published following Strubell et al's influential findings (Verdecchia et al 1). This subsequent wave of attention placed an emphasis on calculating and reporting the environmental impact of AI, in an effort to raise awareness, and hold those responsible, accountable for their actions. Journalists have a crucial role in closely monitoring this area of research, as they are responsible for analyzing, summarizing and communicating this consequential information about AI's environmental impact to their audience.

Analysis of AI Related Emissions

Early research efforts primarily focused on highlighting the carbon emissions associated with artificial intelligence (Thompson et al; Wu et al; Strubell et al). One peer-reviewed study

found that the overall carbon emissions associated with AI-models are steadily rising, increasing from 487 Mt of CO_2e in 2015 to roughly 2,000 Mt of CO_2e in 2022 (Luccioni and Hernandez-Garcia 11). To put this into perspective, in Canada, driving 4500 km (the distance between Montreal and Vancouver) produces 1 Mt of CO_2e (Mahaffy). Although the global ICT sector comprises an estimated 2-4% of the world's GHG emissions, with approximately two-thirds stemming from operational energy use, and the rest originating from material extraction, manufacturing, transportation, and end-of-life processes, researchers have argued that it is crucial to accurately calculate and document these figures in an effort to further understand the extent of this growing industry's environmental impacts (Luccioni and Hernandez-Garcia 1). As investment in AI has drastically increased in recent years, a trend that is expected to endure into the future, understanding and mitigating its environmental footprint becomes increasingly imperative. This surge is exemplified by recent investments into data centers, which act as the backbone of the modern digital revolution. They are responsible for providing crucial infrastructure for the storage, processing, and management of vast amounts of digital information for various purposes (Singh 324). They play a key role in the development, deployment, and operation of AI models, as they are capable of facilitating the computational power required to train and operate these increasingly advanced technologies. According to a 2023 report, "over the last 5 years, spending from market hyperscalers (Google, Amazon, Meta, Microsoft, and Oracle) on data centers has increased by over 25% (increasing from approximately $42 billion in 2017 to $158 billion in 2022)" (Newmark 6). This recent increase in investment can be attributed, at least in part, to the exponential growth and demand associated with artificial intelligence (Joshi).

While the strengthening of the ICT sector's infrastructure allows for the expedited development of AI technologies, the ideology of "obtaining state-of-the-art results in accuracy (or related measures) through the use of massive computational power," has been consistently proven to have adverse effects on the environment and has led some academics to call for more sustainable practices in the realm of artificial intelligence (Schwartz et al 2). Despite the recent surge in research and efforts from the AI academic community to highlight these issues, scholars in journalism studies have yet to give significant attention to the environmental impact in their writings on AI. This lack of focus raises concerns about the thoroughness of discussions surrounding AI's broader implications within the industry. While the total carbon footprint of the field of AI is unclear due to its distributed nature and the lack of systematic reporting of emissions from developers, in the face of the climate crisis, it is important for the AI community to acquire a better understanding of its environmental footprint and how to reduce it. This in turn will help journalists better understand these impacts and communicate them within their community as well as within the public sphere.

In response to the increasing concern about the environmental impact associated with AI, researchers developed open-source tools capable of assessing the carbon emissions of various AI models. Real-time monitoring tools such as Carbontracker and Codecarbon and post-training analysis such as the ML Emissions Calculator, aim to assist the research community in calculating and reporting model emissions (Luccioni et al 1; Wolff-Anthony et al; Hegeurte et al; Lacoste et al). One study utilized the Carbontracker tool, generating the following statement; "the training of models in this work is estimated to use 37.445kWh of electricity contributing to 3.166kg of CO_2e, which is equivalent to 26.296 km traveled by car" (Wolff Anthony et al 2). Despite their availability, these tools are currently underutilized for emissions reporting due to

the lack of data transparency from AI providers, resulting in rough estimates rather than precise figures. As of writing this paper, there are very few examples of journalists addressing this issue, potentially contributing to the underutilization of these tools. Nevertheless, this avenue of research is vital and warrants support from the broader AI community, as it represents one of the few methods available for generating such data. By systematically estimating the carbon footprint of AI models, these tools can help raise awareness, promote the development of energy-efficient software, and minimize resource waste.

Analysis of AI Related Energy Consumption

As researchers delved deeper into the environmental implications of AI, they began scrutinizing the consumption patterns of large-scale AI models alongside their emissions. With increasing computational demands throughout the life cycle of AI, spanning development, training, and operation, researchers observed a heightened reliance on substantial resources such as electricity and water.

The life cycle of artificial intelligence encompasses six key stages: raw material extraction, manufacturing, model development, model training, model deployment, and disposal (Luccioni et al 3). However, due to the lack of data transparency, researchers encounter challenges in accessing data to adequately quantify phases like raw material extraction, manufacturing, and disposal. As the community advocates for more robust disclosure of information from AI contributors, attention has shifted primarily to the data accessible phases, including model development, model training, and model deployment, where significant electricity and water consumption habits have been identified.

Beginning with the energy consumption of the development stage, creating large machine learning models involves complex processes that demand significant energy inputs to function.

This stage encompasses designing, constructing, and refining a model, which includes tasks like data preprocessing, feature engineering, algorithm selection, and evaluation (De Silva et al 4). Given the computational complexity, model development typically accounts for the highest energy usage, as developers engage in extensive trial-and-error experiments and hyperparameter searches to fine-tune their models (Kaack et al 5). For instance, Google disclosed in a 2022 report that 15% of its total energy consumption over three years was dedicated to developing machine learning models (OECD 6). While the initial development phase incurs significant energy costs, it is a one-time expense in the model's life cycle, unlike the training and operation stages.

After completing the development stage, a machine learning model enters a rigorous training phase aimed at refining its predictive capabilities by identifying patterns and relationships within its given dataset. This process employs optimization algorithms to repeatedly adjust the model's parameters, reducing prediction errors and enhancing performance with each iteration (Hazelwood et al 2). The rise of large-scale AI models has led to an exponential increase in computational power requirements for training, which surged by a staggering 6,000,000-fold from 2012 to 2022 and continues to escalate (Rao 1; Sevilla et al 19). The energy consumption during this stage varies depending on factors such as the carbon intensity of the primary energy source and the duration of training, both of which are specific to each unique model and significantly impact the energy requirements (Luccioni and Hernandez-Garcia 11). For example, BLOOM, a 176 billion parameter LLM, underwent training for a total of 1.08 million GPU hours using 384 GPUs, consuming 433,195 kWh of electricity (Luccioni et al 3). In contrast, OpenAI’s GPT-3, another large-scale LLM with 175 billion parameters, was trained for approximately 800,000 GPU hours on 1024 GPUs, consuming

936,000 kWh of electricity (Rigley et al 861). The unique configurations of each model's training parameters directly influenced the energy consumption during this phase. To contextualize these figures, the average household consumes about 10,715 kWh of energy annually (Benningfield et al), which demonstrates the scale at which LLMs consume energy during training. Such energy usage significantly contributes to the emissions generated by AI models, as the location and energy mix of the grid used for training can lead to substantial carbon emissions. For example, considering BLOOM's training process, its 433,195 kWh of energy consumption, when multiplied by the carbon intensity of the energy grid it was trained on, resulted in the emission of approximately 24.69 Mt of CO_2e (Luccioni et al 4). Once again, to help put this into perspective, in Canada, driving 4500 km (the distance between Montreal and Vancouver) produces 1 Mt of CO_2e (Mahaffy). These significant figures offer insight into the overall consumption and emission rates associated with the production of large-scale AI models. As the demand for this technology grows, ICT companies face pressure to meet these demands, thereby exacerbating their already substantial environmental footprint.

Furthermore, in addition to the significant energy consumed during the training process, developers often train intermediate models with different parameters to refine the architecture and hyperparameters of the final model, further escalating AI's energy demands (Luccioni et al 7). Additionally, training is frequently conducted at various intervals post-deployment to maintain the accuracy and relevance of algorithms. For instance, companies such as Facebook have disclosed that their ML models undergo retraining cycles varying from hourly to multi-monthly, with each cycle demanding different levels of energy and resources (Hazelwood et al 5). Although the initial energy consumption may be less intensive compared to the

development stage, the recurring nature of the training process results in a steady escalation of energy consumption over time.

Finally, once a model has completed its development and training phases, it progresses to the operational stage. Here, the energy consumption primarily depends on factors such as the efficiency of the underlying algorithm, the infrastructure facilitating inference interactions, and the energy mix powering the model's operation (Patterson et al 2). During this phase, through a process known as inference, the model receives input from users and generates output, relying on its training to process real-world data and produce accurate and useful responses. Despite being a relatively nascent area of research, studies indicate that the inference stage significantly contributes to an AI model's overall environmental footprint, comprising 50-90% of its carbon costs (Luccioni et al 6; De Vries 2; Yarally et al 1; Natarajan et al 7). Given that the majority of an AI model's lifespan is spent in this phase, these findings are significant, considering that a single large language model (LLM) can consume upwards of 500 MWh of energy per day (Wu et al 3; De Vries 1).

This stage holds particular relevance to the general public, as inference related consumption and emissions are directly influenced by human-machine interactions. Quantifying the footprint of inference is crucial to raising awareness about AI’s environmental implications, and the direct impact that an average user can have. As the integration of AI becomes more widespread across domains such as journalism, AI users should become more conscious of the potential implications of their actions when relying on model inference to automate, augment, and generate their content. However, due to a lack of comprehensive research, fully conveying the inference stage's impact, both current and projected, remains challenging.

Analysis of AI Related Water Consumption

As the discourse on the environmental impact of AI continued to evolve, Li et al. identified water consumption as an emerging topic that added significant depth to the discussion. With severe water scarcity affecting approximately 40% of the world's population, the unfettered expansion of the data center and AI sectors pose cause for concern (Aldaya et al 2). The computational requirements to develop and operate large-scale AI models consume excess amounts of power and produce large amounts of heat in the process, in addition to CO_2e. Recent developments in cooling technology rely on liquid cooling systems to maintain the operative abilities of data centers. Not only is the cooling process responsible for upwards of 40-50% of data center electricity usage, it is also responsible for the annual consumption of billions of litres of water, with companies such as Microsoft and Google reporting annual increases in usage ranging between 20-30% (Zuccon et al 3; Monserrate 1; Henderson et al 4; Li et al 2). A prime example of the sector's water consumption came when Google met significant backlash after they proposed constructing a state-of-the-art data center in Uruguay, as the country was in the midst of its worst drought in the last 74 years (Livingstone). The proposed data center was estimated to consume 7.6 million litres of Uruguay's drinking water per day to cool its servers, when water shortages were already so severe that the government had resorted to supplying the public with fresh water mixed with sea water, prompting widespread protests (Livingstone). In response to these protests, Google released a statement claiming that it had redefined the size of the data center and switched to an air cooling system, which have also been proven to be accompanied by a litany of embodied emissions due to their reliance on regional climate factors (Butler; Li et al 4). This example vividly illustrates the significant impact that the consumption habits linked with AI can have on communities. While the benefits of these technological

advancements are substantial, there is a pressing need to raise awareness about the tangible environmental and societal impacts that these technologies and their infrastructure can have.

While these figures provide an idea of the level of water consumption from data centers as a whole, Li et al provided a comprehensive breakdown of the water consumption of a single AI-model. Through analyzing the training and deployment of OpenAI's GPT-3, they estimated that its training process consumed 5.4 million litres of water, consuming an additional 500 ml of water per every 10-50 user inquiries. These numbers have likely since increased as a result of OpenAI releasing their new model, GPT-4, which was trained on 1.76 trillion parameters compared to GPT-3's 175 billion. Seeing as the exceedingly popular AI program ChatGPT is powered by the GPT-4 model, we can assume that this inference based consumption adds up quickly, seeing as the platform gained over 100 million users within 2 months of its release (Li et al 5; Hu).

Overall, the exploration of artificial intelligence's water consumption is a relatively new field that has yet to receive the attention it merits. While existing research predominantly centers on energy consumption and carbon emissions, the impact of AI on water resources is equally crucial, with far-reaching global consequences. Researchers and journalists must collaborate closely to fully ascertain the scope of this issue and to disseminate any new findings to the public. As awareness of these issues grows, there is a greater likelihood that the global community will become more attuned to the negative impacts of AI and be motivated to take the requisite measures toward a more sustainable future.

Section 3: Addressing the Gap

Armed with a nuanced understanding of artificial intelligence's environmental impact, it is time to contextualize these issues within the realms of journalism and sustainable development. As the news industry progressively adopts AI technologies, aligning with the widespread integration observed across various domains, a spectrum of ethical concerns has emerged within the community. However, amidst these discussions, the environmental footprint of AI, a crucial aspect of the conversation, has been largely neglected.

Despite the news industry's relatively small contributions to the growing demand for AI technologies and their environmental implications compared to other sectors, journalism holds a unique position in society due to its influential role in informing and shaping public opinion. Current trends in artificial intelligence have been proven to be unsustainable and detrimental to the future of our planet. Nevertheless, as the world continues to grapple with the realities of climate change, AI is often hailed as a modern solution (Mastrola), despite its substantial contribution to GHG emissions and finite resource consumption. While the academic community recognizes AI's potential to harm the environment, the journalism community has been preoccupied with internal ethical debates, routinely neglecting their role in the exacerbation and possible mitigation of a largely external issue. As the realities of the environmental impacts of AI continue to come to light, journalists need to become more aware of the developing situation and prioritize demystifying these complex concepts to better educate the general public. Ideally, through raising awareness about this developing issue, more pressure can be placed on the ICT industry to become more forthcoming about the implications of their actions and to begin to implement more sustainable practices. With this goal in mind, the following section of this paper will work to demonstrate some promising paths forward that maintain the innovative promise of

artificial intelligence while simultaneously prioritizing the mitigation of its ecological implications to promote a more sustainable future.

Working Towards Sustainable AI Practices

Sustainable development is defined as development that fulfills present needs while safeguarding the capacity of future generations to fulfill their own (van Wynsberghe 3). First and foremost, to enable the development of sustainable practices for the field of AI and all of its subsequent users, it is imperative that researchers and contributors have a common understanding of the current untenable practices that permeate the field. As Verdecchia et al's study, *A Systematic Review of Green AI,* demonstrates, researchers have recently begun to commit more resources towards understanding the environmental impact of artificial intelligence, yet a common theme has been pervasive throughout. Analysts are struggling to understand the breadth of this issue as a result of a lack of data transparency from major ICT companies and other contributors. A reluctance to divulge key data required to dissect these issues has proven to be a major obstacle in the pursuit of sustainable AI. As Mark Graham writes, "consumers are usually only able to see commodities in the here and now of time and space, and rarely have any opportunities to gaze backwards through the chains of production in order to gain knowledge about the sites of production, transformation, and distribution" (Graham 1; Crawford and Joler 11).

Nevertheless**,** researchers have maintained the course and worked to provide meaningful findings, relying on the information that is made available to them. Said research points towards three main pillars for developing actionable sustainable practices within the AI industry; the standardization of environmental impact reporting and data transparency, the improvement of existing and future AI infrastructure, and the identification and adoption of best practices. While

the following section will explore each topic, offering context on why they are deemed essential for the future of sustainability, it is also important to delineate the role journalism must assume in addressing them.

In considering the tensions surrounding the intersection of journalism and advocacy, it is essential to acknowledge the complexities inherent in journalists sharing information that may lead to major societal changes. Traditional notions of journalistic objectivity often limit journalists in their ability to advocate for specific causes. However, journalists still play a vital role in providing the general public as well as advocacy groups with information that can be utilized to influence change, thereby helping to fill gaps in traditional media coverage (Ingram). In today's diverse media landscape, there is a growing recognition of the need for journalists to not only report on issues but also engage with the public to facilitate positive change. This evolution aligns with the principles of public journalism or engagement journalism, wherein journalists actively seek to involve the public in discussions about pressing societal issues, such as the ethical and environmental impacts of AI (Rosen 381; St. John et al 95; DeClercq et al). However, it is imperative to navigate these roles with careful consideration of potential conflicts of interest and biases, ensuring that future endeavors are transparent and rooted in ethical principles.

Moreover, while journalists undoubtedly have a role to play in promoting sustainable AI practices, it is equally important to recognize that other stakeholders, including AI developers, technology companies, policymakers, and consumers, also bear responsibility. By fostering collaboration and collective action among these various actors, we can work towards a more sustainable future for AI-driven technologies, where ethical considerations are prioritized and environmental impacts are minimized.

Path A: Standardized reporting and data transparency

The totality of the environmental impact of artificial intelligence remains largely unknown as a result of a lack of data transparency across the ICT industry. Various factors contribute to this opacity, including but not limited to; the protection of proprietary technology, the avoidance of negative public perception, regulatory concerns, the prioritization of short-term profits over long-term environmental impact, and a general lack of standardized metrics (Lacoste et al 4). This scarcity of information has led to a significant gap in public awareness regarding the environmental implications of AI, however, journalism has the potential to catalyze change in this regard.

By leveraging its investigative prowess and significant public reach, a targeted effort from the journalism community stands to generate the attention required for the public to demand the development and integration of a standardized reporting system. This system would not only encourage industry stakeholders to consistently disclose crucial information related to the environmental consequences of their actions but also enhance overall accountability while empowering the public to scrutinize AI's environmental impacts. By engaging the public, journalism serves as a vital catalyst for discussions on ethical and environmentally conscious practices within the AI industry. Through uncovering and disseminating vital yet underreported information, journalists can equip the public with the necessary tools to mitigate the impacts of the expanding influence of artificial intelligence.

Wu et al contend that the industry requires “easy-to-adopt metrics to make fair and useful comparisons between AI innovations” (Wu et al 10). Although there is no universally accepted approach for assessing the environmental impact of AI, Walter Klöpffer’s redefined version of a life cycle assessment (LCA) provides researchers with a strong guiding framework to take a

holistic approach towards comprehending and reporting the impacts of this rapidly evolving field. The LCA methodology asserts that "all environmental burdens connected with a product or service have to be assessed, back to the raw materials and down to waste removal" (Klöpffer 223). To facilitate the standardized employment of this method, ICT companies must provide the research community with access to the necessary information to conduct a comprehensive life cycle assessment from "cradle to grave."

According to Roel Dobbe of the AI Now Institute at New York University, similar practices to those being proposed are already commonplace in industries with comparable environmental implications, such as the aerospace sector. He argues that estimating the environmental footprint of AI technologies should be relatively straightforward, given that ICT companies and AI developers already possess the detailed metrics necessary for accurately calculating and reporting industry emissions and consumption patterns (Dhar). However, implementing such transparency across the industry will require political will and heightened consumer awareness, as Dobbe suggests.

As previously mentioned, journalism could play a pivotal role in fostering this transparency, yet research indicates minimal attention has been given to these ethical considerations, exacerbating the current state of informational opacity within the AI sector. By universally disclosing their resource consumption and CO_2e footprint, tech companies could level the playing field, enabling both the research community and the public to better understand the true implications of the industry's rapid expansion. Through collectively lobbying AI’s stakeholders to be universally transparent about the environmental impact of their actions, we provide our communities with the choice to accept or deny their innovations. While artificial intelligence offers significant benefits across various domains, decisions with the capacity to

impact the future well-being of our planet should not solely rest with private entities. This sentiment is shared across a plethora of peer-reviewed studies (Henderson et al; Luccioni and Hernandez-Garcia 12; Rohde et al 8; Kirkpatrick et al), and it deserves to be taken seriously in an attempt to educate the public and raise awareness about the realities of the artificial intelligence boom.

Path B: Improving Infrastructure

Another consideration for the prospect of achieving sustainable AI practices is the general improvement of AI infrastructure (Lacoste et al 51; Patterson et al 2). Through investing in more energy efficient hardware such as processors, servers, and data centers, ICT companies can aim to reduce the environmental impact of their actions while promoting sustainable AI practices. Although this method of impact reduction is accompanied by challenges such as high capital costs, intermittency of renewable energy, location constraints, and technological obsolescence, to name a few (Vincent et al 5), it is a worthwhile endeavor to allocate more resources and research towards sustainability.

To bridge the gap between AI infrastructure improvements and journalism, news organizations can contribute in several ways. In a parallel approach to "Path: A," the community can utilize its resources and extensive public reach to raise awareness about the benefits of adopting more efficient technology, ideally leading to systemic change. Through highlighting existing research and stimulating fresh and more consequential investigations as a result, the journalism community finds itself in a unique position to equip the public with the necessary information to encourage AI stakeholders to prioritize energy-efficient hardware and sustainable data center practices.

Additionally, the journalism community can lead by example by implementing eco-friendly AI infrastructure in their own operations and reporting on the benefits and challenges of such initiatives. By highlighting the importance of sustainable AI infrastructure in its news coverage, the journalism community can raise awareness among both industry stakeholders and the general public, fostering a culture of environmental responsibility within the AI sector.

Path C: Identifying and Adopting Best Practices

Beyond providing more robust reporting on the need for a standardized reporting system and the benefits of improved infrastructure, journalism can significantly contribute to the sustainability of the AI industry by highlighting a list of best practices and their potential impacts. Journalists can utilize their platform not only to identify these practices but also to investigate and reveal which major AI contributors adhere to them and which ones fall short, further educating the public. The following section will outline several key best practices and illustrate their importance for the future of sustainable AI.

An emerging trend in the industry is the emphasis on renewable energy grids, aiming to steer companies away from fossil fuels. With the escalating computational demands of AI, greater energy consumption is inevitable for the production and operation of large-scale models. Prioritizing the siting of data centers in regions powered by carbon-free sources like hydro, wind, and solar energy presents an opportunity for the industry to diminish its carbon footprint and advance sustainable AI practices (Patterson et al 2). However, it is important to note that transitioning to carbon-free energy sources faces challenges due to the scarcity of rare metals and materials, as well as the substantial economic investment and time required for infrastructure development (Wu et al 6). Nonetheless, even with these limitations, implementing this

proposition on a smaller scale holds promise for mitigating the long-term environmental impacts of AI.

Another significant sustainability practice in the field of AI involves carbon offsetting. ICT companies such as Google, Meta, and Amazon have made efforts to purchase renewable energy credits (certificates that represent the generation of a specified amount of renewable energy) which theoretically match and offset every unit of non-renewable energy consumed by data centers and other key infrastructure (Wu et al 6). Although this is a valiant endeavor, some researchers contend that buying these offsetting credits is useful in reducing a model's carbon footprint on paper, but the process does not actively work to reduce carbon emissions overall, prompting further action towards reaching truly sustainable practices (Luccioni et al 49).

In addition to a heightened awareness of the energy sources powering training grids and the acquisition of offsetting renewable energy credits, the geographical placement of data centers is emerging as an equally crucial factor in this effort towards sustainable AI. For example, servers located in North America can emit anywhere from 20g CO2eq/kWh in Quebec, Canada, to 736.6g CO2eq/kWh in Iowa, USA (Lacoste et al 2). This large discrepancy in energy efficiency can have a significant impact on the overall emissions of an AI model, and should become a deciding factor when selecting the location of AI production and operation. As demonstrated by Henderson et al, ML training is not usually latency-bound, which means that ICT companies have the capability of housing their models in regions that are geographically far away from where they are eventually implemented with negligible impact on performance. By removing this barrier, companies may be more willing to implement these practices in pursuit of embodying sustainable AI practices.

The outlined best practices offer actionable solutions with promising potential to mitigate certain aspects of AI's environmental impact. As it currently stands, it is imperative that the journalism industry utilizes its platform to inform the public of these issues and their proposed solutions. Through providing the public with the necessary tools to critically engage in discussions surrounding the sustainability of AI, we stand a greater chance at reducing future harm and holding major contributors accountable for their actions while maintaining the promising potential of this exciting technology. Additionally, journalism's research community can place more emphasis on the outlined issues and continue to publish relevant research that investigates the existing AI landscape within the industry and highlights potential paths forward that point towards sustainable practices. By shifting their coverage of artificial intelligence in this direction, the greater journalism community can play a crucial role in promoting a balance between technological advancement and environmental sustainability, safeguarding the health of our planet while allowing for continued innovation.

Conclusion

The integration of artificial intelligence in journalism signifies a pivotal juncture in the industry's evolution, offering both unique opportunities and challenges. While the journalism community has engaged in ethical discussions about AI's impact, this paper underscores a consistently neglected aspect of the conversation. As demand for this transformative technology rises, so does the industry's embodied carbon emissions and resource consumption patterns, posing a tangible threat to our planet's well-being. Given the limited research available on this topic across disciplines, there is an urgent need for further investigation and the development of potential solutions. While journalism may seem to have a minor influence on AI's environmental footprint, its intrinsic ability to champion sustainable AI practices emerges as a critical aspect of

this discourse. Through promoting transparency, accountability and collaborative action, journalism can shed light on opaque industry practices and bridge the gap between stakeholders and the public, facilitating a space for informed discussion. By addressing AI's environmental consequences through collective action and informed decision-making, we can harness the transformative potential of AI while safeguarding our planet for future generations.

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