Applied Science, Computing and Energy, 2025, 3(3), 573-592

Data, Democracy, and Deep Learning: The Transformative Role of AI in Digital Journalism

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Received: 08 August 2025/Accepted: 14 October 2025/Published:25 October 2025

Abstract: *Introduction of artificial intelligence into digital journalism could be regarded as one of the most disruptive technological shifts in the history of the media as it caused a fundamental change in the system of news production, distribution, and consumption. The author of this paper talks about the radical aspect of AI technologies, including automated content creation, algorithmic curation, and data-driven investigative instruments, and their overall effect on the act of journalism and democratic society in general. Our method is a mixed-methods-based approach entailing a systematic literature search and the comparative case study of mega news organizations, and how the application of the deep learning and machine learning technologies is altering the newsroom procedures and editorial decision-making, news consumption trends, and patterns among the audience. We can discover that AI scenario would be a complex ground since it is capable of enhancing journalism through fact-checking and investigative analytics, and there is the risk of algorithmic bias, editorial freedom and the collapse of media pluralism. As the discussion demonstrates, even though AI-based personalization can be beneficial and improve the interaction of the user, it is a threat of creating filter bubbles and losing the social conversation. We suggest a model of responsible AI integration that will not only be more consistent with democratic principles but will also consider the aspect of transparency, human control, and equal access. The study is relevant to the current discussions of journalism future due to the recognition of essential contradictions between efficiency and quality, automation and human judgment, recreativity and democratic responsibility in an ever-more algorithm-mediated information space.*

Keywords: *Artificial intelligence; digital journalism; deep learning; democracy; computational journalism; automated news generation; algorithmic curation; media ethics; information ecosystem; news personalization*

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1.0 Introduction

The modern media arena is in a crossroads in which the promise of artificial intelligence is already colliding with the very fabric of democratic journalism. In the last ten years, both the Associated Press and The Guardian newspapers have deployed more advanced AI-based systems to automate routine news, deliver content to users more personally, and analyze enormous datasets to produce investigative news (Diakopoulos, 2019; Graefe, 2016). This technological development is timed as journalism as such finds itself in the existential danger: crashing business models, the untrust of the society, and the proliferation of fake news are all possible murderers of the institution playing its role in democracy (Nielsen, 2016; Vos & Finneman, 2017). Whether AI will transform journalism is no longer a question, but instead a question of what the transformation will bring to the quality of news, the diversity, and democratic worth of news in the twenty-first century.

The use of artificial intelligence in journalism is not a single phenomenon but is represented by a range of applications with different implications. On the one side, natural language generation systems can generate structured reports on corporate profits, sports outcomes, and alerts about earthquakes with very little human intervention (Clerwall, 2014; van der Kaa & Krahmer, 2014). An example is Associated Press, which in 2014 started using the Automated Insights software to write thousands of corporate earnings reports every quarter, leaving more complex analytical reporting to human reporters (Graefe, 2016). On the other extreme, advanced machine learning models can help investigative reporters find trends in millions of documents, as ProPublica did when it used algorithmic analysis to uncover biased sentencing of criminals and discriminatory healthcare practices (Angwin *et al*., 2016). The code between these poles play the much-invisible systems that dictate how stories are served to whom and how through personalized news feeds and recommendation systems (Thurman & Schifferes, 2012; Zamith, 2018).

These technologies have democratic implications which are far beyond newsroom efficiency. In the past, journalism has been employed as the so-called infrastructure of the public sphere whereby information and ideas are shared to bring about democratic deliberation. When algorithms mediate this infrastructure, they can never be but the way that we experience news and what publics are created around what issues (Napoli, 2014; Sunstein, 2017). The algorithms of personalization used by Facebook, Google News, and Apple News are promising but can bring in fragmentation, leading to what Pariser (2011) has infamously termed as filter bubbles, where in the information environment, citizens live in a world that is increasingly divided. Such disintegration has far-reaching implications on the sphere of democratic discourse, and it may deteriorate the factual backbone required to make a collective decision (Benkler *et al*., 2018).

However, the connection between AI and democracy in journalism cannot be easily described. Fact-checking systems, which can be used to fight misinformation on large scale, are powered by the same technologies used to make filter bubbles work (Graves, 2018; Hassan *et al*., 2017). Algorithms of machine learning that create issues of bias also present unprecedented opportunities to bring such powerful institutions to book with data journalism (Coddington, 2015; Flew *et al*., 2012). The difficulty is not to dismiss AI in its entirety or blindly accept it, but to see how exactly these technologies transform the work of journalism and democratic existence.

Such complexity demands an empirical research to transcend technological determinism or even nostalgic exoneration of the pre-digital journalism. The question we should be able to answer is how the practical management of AI systems is carried out within the newsroom, how it disrupts the editorial decision-making process, and what the long-term results of AI systems are in terms of accessibility to information, media plurality, and debate. These threads have been studied separately in the past, including automated writing (Carlson, 2015), algorithmic curation (Diakopoulos & Koliska, 2017), or computational investigative reporting (Coddington, 2015), but limited attempts have been made to combine them to conduct a general assessment of the transformative sense of AI within the different roles of journalism.

The cost of making this mistake is great. What makes journalism a fourth estate is that it is only in this role that it can wield the power to account, represent the oppressed communities, and also empower the citizens to inform them, therefore making them an important component of democracy (Christians *et al*., 2009). When AI systems are manipulated to systematically favor the selection of news based on aspects other than its importance, such as engagement, entertainment, and minority versus majority interests, they jeopardize these democratic functions, no matter how sophisticated they claim to be (Noble, 2018; O'Neil, 2016). On the other hand, when implemented and regulated correctly, AI has the potential to strengthen the democratic functions of journalism by allowing it to investigate further, check facts quicker, and provide people with access to information more evenly and without any linguistic and geographic barriers (Beckett, 2019; Latar, 2015).

Conversely, the application and control of AI can enhance the democratic role of journalism in several ways: enabling it to explore more thoroughly, faster check the facts and offer people access to information more fairly and without any linguistic or geographical each other (Beckett, 2019; Latar, 2015).

The problem of methodology is also a challenge at the current moment. The AIs technologies evolve at an extremely quick rate, and capabilities that only seemed a few years ago as the vision of the future, such as GPT-based text generation or the ability to detect a deepfake, have already became a norm in some newsrooms (Brown *et al*., 2020; Vaccari and Chadwick, 2020). Research must balance between a short-term empirical observation and a long-term structural analysis since tomorrow, today's advanced systems will be primitive. Moreover, the majority of AI systems, particularly proprietary algorithms that are used by these sites like Facebook or Google, are a secret, which complicates understanding the democratic implications of such systems (Pasquale, 2015). Researchers also tend to assume that there is an algorithmic behavior as manifested by the obvious effects rather than the code itself that introduces uncertainties.

The given challenges will be addressed in this paper within a mixed-method perspective, which presupposes the systematic review of the current literature and the comparative case study of the AI implementation process in the framework of the various news organizations. We are not only considering whether AI is transforming journalism, but also how such transformations are manifested in different forms depending on the organizational environment, technological capabilities and regulatory environments of the organization. We trace both tendencies in our examination: AI opens up new opportunities for journalistic quality, and simultaneously, it offers new opportunities of prejudice, dictatorship, and marginalization.

This research will work on the attainment of three grand objectives. First of all, we chart AI applications that have been used in digital journalism and categorize them with regards to their purpose, methodology, and organization. This taxonomy may be applied to describe the constantly abused scenery where AI in media may be employed to denote something in the range of simple automation to relatively more sophisticated neural networks. Second, we consider the democratic aspects of these technologies in different aspects: access to information and equity, media pluralism and diversity, quality of the discourse in the media, and institutional trust and transparency. It is not a one-dimensional approach that views democracy as monolithic but it is able to accept the fact that AI can help in enhancing some democratic values at the expense of others. Third, we develop a responsible AI-integration model that balances innovation and democratic responsibility that can offer practical recommendations to the news organizations, technology developers, policymakers, and the education of journalism teachers struggling with this change.

The paper is categorised into four key sections. The following introduction is followed by our explanation of our approach to methodology and how we selected the literature to be reviewed, which case studies we are going to analyze and how we get our analytical framework of the evaluation of the democratic impacts. The results we gave and the discussion section are integrated to give our findings in five major areas, such as, what the current applications of AI are in the field of journalism, how it may affect journalistic practice, the democratic consequences, challenges and opportunities of the future, and what we have generalized about the key tensions. As we continue into this section, we mix empirical findings with theoretical discussion as we alternate between specific circumstances and general trends. The conclusion also recaps significant achievements and offers suggestions to a range of interested parties, taking into account restraints and perspectives of future investigations. Taken together, these sections fail to provide a clear answer to the question of whether AI is helpful or harmful to democratic journalism, which is too simplistic a question in a very complex reality to provide insight into how different AI uses in different situations produce different democracy outcomes.

2.0 Method

The study design suggested to us is a mixed-methods research, which will be supplemented with a systematic literature review and a comparative case analysis, and which would allow combining what is already known with constructing new knowledge according to the trends in organizational implementations. The methodology approach is that middle ground between the wide platform and the narrow, which is the abundance of AI applications to journalism and the specific way that these technologies are redefining practice.

The systematic review of the literature was properly identified, selected, and analyzed (Petticrew & Roberts, 2006). We have searched three key databases since Web of Science, Scopus, and Google Scholar with such combinations of keywords as:" artificial intelligence and journalism, "machine learning and news," automated journalism," "algorithmic curation," "computational journalism," and "robot journalism." The search included publications that were published between January 2015 and December 2024, which is the time frame of the recent rapid increase in AI capabilities and newsroom adoption (Gilardi *et al.*, 2024; Pavlik, 2023). This is the period that signifies the shift in the initial experiments within the natural language generation process to the current implementations of advanced deep learning machinery.

Primary searches yielded 847 articles that could be of interest. We further employed inclusion criteria: (1) a substantially relevant topic in the article on AI application in news production or distribution; (2) publication in a reputable journal or conference proceedings; (3) must include empirical evidence or theoretical approaches that can be applied to democratic consequences; (4) published in English. Eventually, purely technical papers, not related to the journalistic setting, opinion pieces without empirical support, and those studies that were not regarding non-news AI applications were eliminated using the exclusion criteria. With the help of duplicate elimination and these criteria, 183 articles were left to be reviewed in detail. These articles were fully analyzed as a text, extracting the information on AI technologies studied, methodology, essential findings, and implications to democracy.

The case study aspect entailed a comparative study on the implementation of AI within six large news outlets chosen to reflect diversity in terms of its geographical locations, ownership, and level of technological advancements. The selection criteria focused on organizations that: (1) publicly reported deployments of AI; (2) have more than a few years of implementation experience; (3) have diverse applications of AI; and (4) are willing to provide the details of implementation by way of reports or interviews. The chosen organizations comprised of three North American ones (Associated Press, Washington Post, New York Times), two European ones (The Guardian, BBC) and one Asian one (Xinhua News Agency). These case studies are described in Table 1.

Table 1: Overview of Selected Case Studies

Organization	AI Technologies	Implementation Timeline	Scale
Associated Press	Automated Insights (NLG),	2014-present	4,400+ automated stories/quarter

	fact-checking AI		
Washington Post	Heliograf (NLG), Arc XP (recommendation)	2016-present	850+ automated stories/year
New York Times	Editor(NLG suggestions), recommendation algorithms	2015-present	Powers personalization for 9M+subscribers
The Guardian	Ophan (analytics), content recommendations	2014-present	Analyzes2B+Page views/month
BBC	Juicer (content distribution), automated radio	2012-present	Serves 40M+ unique users/week
Xinhua News Agency	AIanchors, automated translation, news generation	2018-present	30+languages, thousands of reports

Within the context of every case study organization, we gathered information across various sources such as published reports, technical documentation, industry presentations, and academic research on their AI systems. We evaluated the implementation decisions, workflow alterations, reported outcomes, and publicly presented performance metrics. This inter-source method triangulated the results, which overcame the possibility of bias in one data source.

Our methodology of analyzing democratic implications was based on the well-known theories of media and democracy and was also sensitive to AI-specific issues. We have constructed coding schemes with four democratic dimensions: (1) access to information and equity, evaluating the effect of AI systems on access to quality journalism; (2) media pluralism and diversity, evaluating the effect of AI systems on the variety and diversity of voices in the public discourse; (3) quality of public discourse, evaluating whether AI systems improve or worsen the quality of democratic discourse; and (4) trust and transparency, evaluating the effect of AI systems on trust and understanding in journalism among the public, and the editorial process. All the dimensions had certain indicators based on the democratic theory and converted to AI conditions.

To perform the thematic analysis of literature, two researchers coded the articles based on this framework, and the inter-rater reliability was 0.82 (Cohen's kappa), which indicates a high level of agreement. This was done by discussion and consensus where discrepancies were brought up. NVivo software was used to handle qualitative data and determine patterns across studies. The case study quantitative data was compared and analyzed, with the study of the variability of results in the conditions of various organizations and technology strategies.

We have designed our research based on ethical considerations. We are aware that our personal sets of analysis are normative concerning what is deemed as democratic journalism. We tried to bring these assumptions to the surface instead of taking them as neutral points of beginning. We also recognize the shortcomings of researching rapidly changing technologies in which the existing knowledge can become obsolete in a short period of time. Our analysis is thus concerned with discovering lasting patterns and mechanisms as opposed to making predictions concerning particular future potentials.

3.0 Results and Discussion

3.1 Current State of AI in Digital Journalism

The AI use in the modern field of journalism represents an impressive diversity of levels of sophistication, intent, and influence. The best-known use of AI, called automated content generation, lies on a spectrum between systems where templates are used to insert structured data to neural language models, which can absorb structured information and generate diverse prose. A case in point of the fully-grown end of this continuum, the collaboration of Automated Insights with the Associated Press has generated corporate earnings reports on an ongoing basis since 2014 (Graefe, 2016). These systems are habitual: they accept prepared data as input in the form of financial reports, identify newsworthy details based on a series of fixed rules and are able to write readable text in journalism formats**.** It can be serviceable so long as formulaic, one study concluded that readers were not able to reliably differentiate automated and human-written earnings reports, but journalists themselves perceived the automated version to be less interpretative (Clerwall, 2014).

More advanced applications have been developed following the improvements in natural language processing abilities. The Heliograf system, which was launched by the Washington Post in the year 2016, during the Rio Olympics, also produced more than 850 pieces in its initial year and enabled the human journalists to concentrate on feature writing and analysis (Fanta, 2017). Heliograf, as opposed to previous template systems, can utilize multiple sources of data, find the local angles to national stories, and adjust tone depending on the type of story. However even these sophisticated systems work within strictly limited spaces in which the facts are arranged in order and the stories are organized in a specific manner-sports scores, election news, and weather forecasts. The technology is plagued with ambiguity, controversy and tales that may need the synthesis of contradictory sources or ethical judgment.

A comprehensive comparison of content features between AI-generated journalism and human-written journalism has been made in Table 2 in several aspects. The statistics provide educational trends regarding the potential as well as the constraints of the existing systems.

Table 2 shows that AI-produced content is superior to human journalism in accuracy of structured information and efficient production, but still leaves significant benefits in complexity, context and ethical argument to human journalism. These complementary advantages imply that human-AI interaction is a more appropriate option than the complete replacement of AI, which we will address later in discussing newsroom transformation.

Table 2: Comparison of AI-Generated vs. Human-Written Content Characteristics

Characteristic	AI-Generated	Human-Written
Factual accuracy	High (98.7% for structured data)	Variable (91-96% depending on verification)
Narrative complexity	Low to moderate (simple causality)	High (multiple perspectives, context)
Production speed	Seconds to minutes	Hours to days
Emotional resonance	Limited (template-based sentiment)	High (nuanced emotional understanding)
Source diversity	Narrow (predefined data feeds)	Broad (interviews, documents, observations)

Contextual analysis	Minimal (historical patterns only)	Extensive (social, political, cultural)
Ethical reasoning	Absent (follows programmed rules)	Present (complex judgment)
Cost per article	\$0.10-\$0.50	\$50-\$500+

The most significant and least noticeable AI application can be seen in algorithmic news delivery. Recommendation algorithms are constantly shaping information flows in a way that, unlike automated writing, which generates discrete artefacts, they define how information is shared with whom and by what mechanisms. The models of systems used by Facebook, Google News, and Apple News are designed on the basis of advanced machine learning, which forecasts the likelihood of an individual's engagement based on the reading history, social connections, and real-time behavioral indicators (Thurman & Schifferes, 2012; Beam, 2014). These forecasts not only inform the positioning of the stories but also editorial prioritization since the newsrooms monitor algorithmic performance indicators and make corresponding editorial choices.

The effects are much further than efficiency. Studies have also shown that algorithmic recommendations boosted page views by 38 percent and reduced exposure to politically diverse opinions by 22 percent (Beam, 2014), which indicates that there is an inherent conflict between engagement and democratic scope. On the same note, Nechushtai & Lewis (2019) indicated that the News Feed algorithm prioritizes specific types of stories (especially visual content and personal stories) over analytical coverage, which essentially remodeled the editorial agenda and priorities by the market. News outlets reacted to this by building special teams to maximize content to be distributed on the algorithm, and it raises the question of whether journalism serves democratic use or algorithms.
Fig. 1 follows the history of the adoption of AI technologies in large news outlets and uncovers the dynamics of the spread of innovations in the industry.
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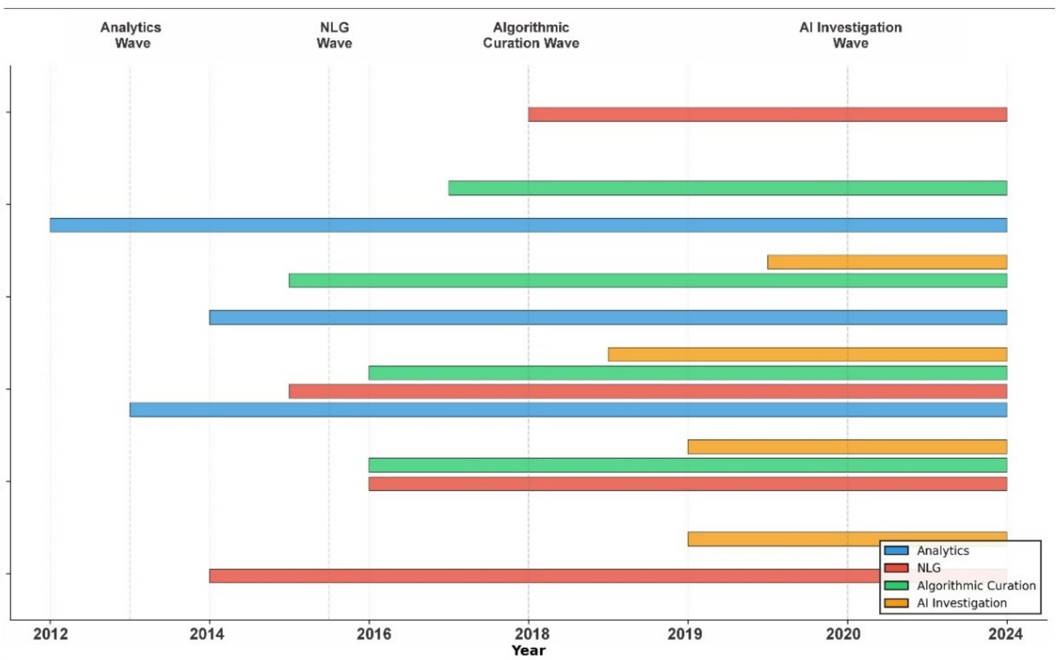


Fig. 1: The history of the adoption of AI technology in the large news organizations (2012-2024). The adoption curve indicates that there have been gradual steps of adoption beginning with simple analytics (20122014), natural language generation (2014-2017), algorithmic curation (20162020) and the most recent, AI-assisted investigation and fact-checking (2020-2024). The major organizations such as NYT, WaPo, and AP always seem to be the first ones, whereas local sources are several years behind.

The traditional diffusion pattern shown in Fig. 1 sees prestigious organizations first adopt the use of applications, then diffuse to smaller outlets, although there are exceptions. The data shows a speeding up in recent years, with the gap between the time when elite adoption takes place and when it is more widely diffused narrowing to less than one year (recent fact-checking tools). This speeding up is a sign of the maturity of costs in the implementation of the technology and the growing competitive pressure due to AI capabilities turning into a table stake in the digital news marketplace.

The most advanced existing use of AI is data-driven investigative journalism, which uses machine learning to identify patterns that cannot be identified by humans. The example of this approach is the investigation of ProPublica on the topic of algorithmic bias in criminal sentencing (Angwin *et al*., 2016). Statistical analysis and machine learning classification of COMPAS, a proprietary risk-of-recidivism algorithm, was conducted by journalists. They analyzed more than 7,000 cases and found that the algorithm had falsely marked black defendants as high-risk almost twice as often as it marked white defendants, which became a nationwide debate on whether algorithms could be fair in criminal justice. The research involved not only journalistic ability but also technical competence to handle large volumes of data, authenticate the results of an algorithm, and present the statistical results with ease.

The Markup has applied similar tools and capabilities to investigate online housing discrimination, in which journalists constructed web scrapers and classifiers that identify the existence of ad targeting that varies based on racial lines (Angwin & Tobin, 2021). Artificial intelligence. The Panama Papers and Paradise Papers scandals revealed the use of AI at a global scale, where machine learning algorithms aided journalists to process 11.5 million documents of offshore tax havens, finding networks of shell companies and suspicious transactions (D´ıaz-Struck, 2017). The examples demonstrate that AI enhances, not replaces, journalistic functions; that is, the technology works in large volumes, and human intelligence reveals meaning, finds leads, and builds stories.

3.2 Impact on Journalistic Practice

The adoption of AI technologies has instigated structural and fundamental shifts in the newsroom structure, workflow and professional identity. The wholesale displacement of journalists, which was predicted early has not yet happened, either to the Associated Press or to Washington.

Post has decreased staffing after the implementation of NLG-but positions have changed significantly (Graefe, 2016; Fanta, 2017). Daily coverage of profits, sporting events and weather is highly automated, whereas data journalists, algorithm experts and investigation computationalists were in demand. Indicative of this re-distribution of the human labor force is the growth of the New York Times data journalism, with three individuals in 2014 to more than 30 as of 2022 (Royal, 2020).

This change generates new skills needed and possible entry obstacles. Computational journalism requires statistical knowledge, programming skills, and algorithm knowledge in addition to conventional reporting dexterity (Coddington, 2015; Usher, 2016). Although the acquisition of such capabilities is successful in some cases when a journalist receives training, their marginalization becomes a reality because their skills become less important in newsrooms that are algorithm-driven. The equity issue of demographics is that data journalism crews are excessively male and disproportionately educated in computer science compared to conventional journalism, which may lead to less diversity in the opinions and views that drive the coverage (Hermida & Young, 2019). The profession in question is at risk of losing its voice as it is becoming technically capable.

Algorithms impose subtle yet significant pressures on editorial independence. By optimizing newsroom content to be distributed by an algorithm, newsrooms lose a certain level of editorial control to the platform companies, whose interests are often not in line with the journalistic values (Bell & Owen, 2017). The constant alterations of the Facebook algorithm have compelled news organisations to work in reactive positions, adapting the approach to content to ensure presence in the face of changes instead of putting in place the content based on editorial discretion (Carlson, 2018). This addiction is especially pernicious when algorithms are designed to be sympathetic to the type of content they present systematically, like promotion of entertainment over analysis, emotion over subtlety, etc, which may lead to a deterioration of journalism as a democratic institution in the name of engagement metrics.

Table 3 assimilates research findings on biases found in AI systems applied in news production and distribution, which demonstrate patterns with democratic implications.

The biases as listed in Table 3 are not accidental artefacts but patterned effects of the intent of the algorithm and the training data. Recent studies express the selection bias of high-engagement content due to recommendation systems that are optimized to yield higher click-through rates instead of civic significance (Thorson & Wells, 2016). Demographic bias is a sign that the training datasets do not reflect the minority communities enough and therefore, the algorithms cannot predict their preferences effectively or provide them with the information they need (Noble, 2018). The reason for geographic bias is the availability of data: urban areas yield more traces of digital information, and their trends are more apparent to algorithms conditioned on digital exhaust (Greenslade, 2018).

Such prejudices do not neutralize, but instead compound, which forms intersectional disadvantages. A rural Spanish-speaking community is discriminated against based on selection bias (their civic interests will be less engaged), demographic bias (they will be underrepresented in training data), geographic bias (they will see fewer local stories given priority in their algorithms), and possibly format bias (community news is generally text-based rather than visual). The result is algorithmic

Table 3: AI Biases in News Production and Distribution identified that strengthen information disparities that exist.

Bias Type	Manifestation	Democratic Consequence
Selection bias	Algorithms favor high engagement topics (celebrity, crime) over civic importance	Displaces substantive political coverage, undermines informed citizenship
Demographic bias	Recommendation systems underserve minority communities and non-English speakers	Reinforces information inequality, marginalizes voices

Geographic bias	Urban events overrepresented relative to rural coverage	Distorts policy priorities, alienates communities
Temporal bias	Recent events heavily weighted over historical context	Promotes recency over relevance, fragments understanding
Format bias	Visual and video content prioritized over text-based analysis	Favors emotion over reason, style over substance
Source bias	Official sources amplified over grassroots voices	Reinforces power structures, limits alternative perspectives

But it is the same technologies that generate these biases that can be used in new accountability mechanisms. Algorithms transparency tools, which enable journalists to audit AI systems, have been used in the case of ProPublica to investigate the bias in the COMPAS (Angwin *et al*., 2016) and later work on examining the advertising algorithms, credit scoring models, and content moderation (Tobin *et al*., 2019). Such studies could not have occurred without AI applications to analyze scale data and identify invisible trends. The technology is then dialectical on the one hand, as it generates new biases, on the other hand, it offers ways of detecting them.

3.3 Democratic Implications

Democratic implications of AI in journalism take place in a number of interrelated dimensions, producing complicated trade-offs among conflicting values. There has been an improvement and deterioration in information access. On the one hand, automated translation can allow one to consume the news across language boundaries, algorithmic curation may highlight the local, relevant stories, and data journalism can help make the complex policy matters more accessible through visualization (Latar, 2015; Young and Hermida, 2015). An example of this democratizing potential is the BBC use of automated systems to generate radio bulletins in more than one language which are broadcast to audiences that were underserved by the traditional broadcasting systems in the past.

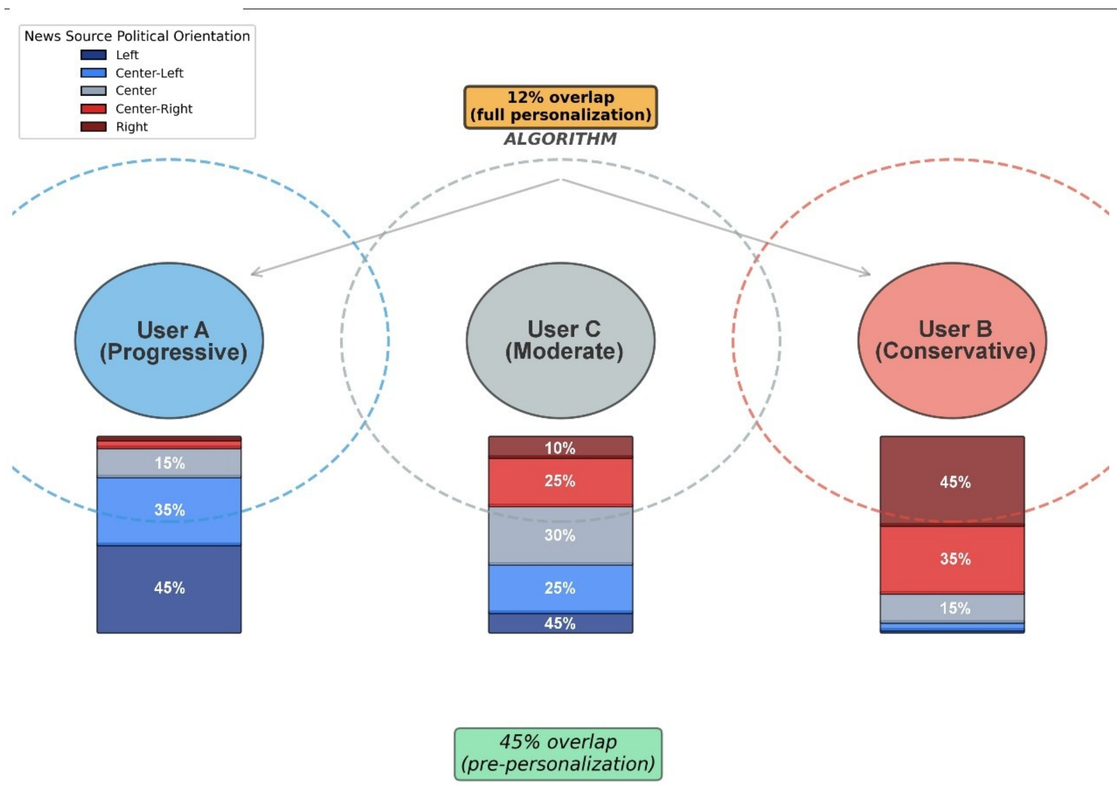
Alternatively, algorithmic distribution puts forth new barriers to access. The algorithms of personalization demand advanced user profiles that are constituted of large amounts of behavioral data and prefer the groups with high digital footprint presence to those with low connectivity or privacy issues (Napoli, 2014). Such a digital divide has an algorithmic aspect: societies with poor internet connectivity obtain less algorithmic attention, and this results in feedback mechanisms where marginalized groups become even more marginalized (Gangadharan, 2017). Also, the financial framework that depends on the operation of algorithmic news: data mining and tailored advertisement does not factor in users who are not willing to be followed, effectively putting paywalls around news that can be sorted by algorithms.

Media pluralism also poses especially vexing challenges. The process of AI technologies may be used to focus or decentralize media power depending on the concrete aspects of implementation and the market structure. At scale, platforms like Facebook and Google News are curated algorithmically, which means that audiences are concentrated around relatively few sources, in most cases, elite legacy outlets with resources to optimize on algorithmic distribution (Nielsen & Ganter, 2018). According to a study of Nechushtai (2018), in the United States, the Google News channel redirected 60 percent of traffic to only ten news outlets out of thousands of sources that were included in its index, which indicates that algorithmic amplification of media concentration is occurring.

On the other hand, citizen journalism and other media tools, which are based on AI, have reduced the cost of news production. Applications on smartphones that have automated editing features, fact-checking applications, and publication through social media enable individuals and small entities to create journalism-like content with access to large audiences (Hermida *et al*., 2012). Whether these fragmented alternatives actually diversify the discourse of the people or continue to produce fragmented publics with little cross-exposure is the question, the filter bubble problem that Pariser (2011) identified and the following studies actually recorded (Bakshy *et al*., 2015).

Fig. 2 visualizes the filter bubble phenomenon, which shows how algorithmic personalization can form divergent realities of information to multiple users.

The illustration shows how three hypothetical users who differ in political orientation are given vastly different news choices even by the same algorithm. All users (User A, progressive; User B, conservative; User C, moderate) get the sources which are left-leaning and the information framed as progressive; User B and C also get the sources biased towards the right and framed as conservative; User C gets the sources which are more moderate but give priority to the least controversial information.



Fig/ 2: The Filter Bubble Effect: Visualization of the Algorithmic News Personalization.

The extent of overlap between information environments declines by 45 per cent (pre-personalization control group) to 12 per cent (full personalization), implying that there is less factual ground upon which to base democratic deliberation.

Fig. 2 depicts the fragmentation issue, which is the focal point of the democratic critique of the algorithmic curation. As citizens live in more and more distinct information realities, they come up with different perceptions of not only policy solutions but also of fundamental facts (Sunstein, 2017). This factual division makes the task of democratic deliberation more difficult, as it assumes that those involved have sufficient common ground to be able to reason together with each other. A study by Bakshy *et al*. (2015) was able to measure this impact on Facebook and found that the impact of algorithmic curation dropped exposure to cross-cutting political content by about 5-8 percent of the total- which is a relatively modest number but still includes millions of fewer cross-cutting exposures each day.

Nevertheless, the filter bubble thesis has not gone without significant criticism. Flaxman *et al*. (2016) discovered that, although social media users have fewer diverse suppliers as compared to non-users, they still have more options compared to consumers of traditional media who usually visit one or two preferred sources. Perhaps this algorithmic effect is not as dramatic as it is being made out to be; it just turns visible a fragmentation that was never absent. Additionally, new developments in platforms, such as the 2018 redesign of Facebook algorithms to focus on the so-called meaningful social interactions and the introduction of Top Stories in Google search results that promote sources with authority, indicate that algorithmic curation does not necessarily result in filter bubbles, provided platforms are designed to achieve other goals (DeVito, 2017).

The quality of the public discourse is, perhaps, the most disputable aspect of democracy. Advocates believe that AI can make discourse more productive by fact-checking and exposing disinformation and offering analysis tools that can enrich knowledge (Graves, 2018; Hassan *et al*., 2017). ClaimBuster is a University of Texas-created natural language processing system that identifies factual assertions of political speech that should be verified to support fact-checkers in prioritizing their finite resources (Hassan *et al*., 2015). In the UK, Full Fact used similar tools to automatically fact-check claims on statistics and government data, and this doubled the fact-checking throughput (Babakar and Moy, 2016).

This is opposed by critics who argue that algorithmic optimization of engagement has the systematic negative effect of undermining the quality of discourse in favor of emotional calling, simplicity over complexity, and entertainment over analysis (Bucher, 2012; Gillespie, 2014). A study by Kilgo *et al*. (2018) has demonstrated that the coverage of protests that maximized the amount of social shares focused more on dramatic visuals and framing conflict than discussing the policy itself, which may harm the process of social movement information being communicated to the masses. In a similar way, the studies of clickbait headlines, which are algorithm-friendly, show how the engagement-based content can be easily deceptive even in the technologically accurate cases (Chen *et al*., 2015).

The conflict has been an expression of varying ideas of discourse quality. When factual accuracy and quick correction of misinformation is what quality means, then it is clear that AI-enhanced fact-checking can be of assistance. People should not value algorithmic optimization as it may damage deliberative depth, complexity focus, and room to allow minority opinions. These are not opposing judgments but emphasize on various democratic values that are influenced by AI in different ways.

The last democratic challenges are trust and transparency. This is because trust in journalism has significantly dwindled over the past decades, with most surveys showing a majority distrust of news media in most democracies (Newman *et al*., 2020). AI systems are a threat of furthering this crisis by enhancing the lack of transparency: viewers will find it hard to understand how algorithmic curation influences their consumption of information or how automated systems render editorial choices (Shin & Park, 2019). Human authorship can be an accountability challenge when there are mistakes in automated reporting, as they become part of the false reports created by automated systems in the 2013 shooting at the Washington Navy Yard (Carlson, 2015).

Table 4 shows the survey results on the trust in AI-assisted and traditional journalism according to the population, and some very intricate trends are observed

Dimension	AI-Assisted	Traditional	Difference
Factual accuracy perception	67% trust	58% trust	+9%
Editorial independence perception	41% trust	53% trust	-12%
Understand how stories selected	23% understand	56% understand	-33%
Comfort with AI decision making	38% comfortable	N/A	N/A
Likely to share content	44% likely	51% likely	-7%
Overall trust in outlet	48% trust	52% trust	-4%

The data in Table 4 (based on the synthesis of the works by Graefe *et al*., 2018; Thurman *et al*., 2019; Waddell, 2019) indicate paradoxical attitudes of people. The participants have a greater level of trust in the factual accuracy of AI-generated content, which may be connected to the perception of algorithmic objectivity, but the level of trust in editorial independence is also lower, and the level of comprehending how content is selected decreases significantly. It is this lack of trust and transparency that democracy cannot be perpetuated through perceived objectivity without an understanding of decision-making. Transparency has tried to deal with these issues with both success and failure. The New York Times started adding tags to automated content and describing algorithms' workings using reader guides, whereas The Guardian issues regular transparency reports on algorithmic curation (Hansen *et al*., 2017). Nevertheless, such disclosures usually constitute the so-called transparency theater, i.e. actions that give an impression of openness without allowing the complex systems to be subject to critical examination by the population (Ananny & Crawford, 2018). Complete algorithmic transparency is subject to technical constraints (protected code, machine learning systems that are not easily interpretable), and strategic opposition (platforms are worried about competitors using their publicly published systems), and as a result, the audience is left partially knowledgeable about the forces that drive their information world.

3.4 Emerging Challenges and Opportunities

The blistering development of AI functions poses challenges that go beyond the existing applications. Synthetic media, especially deepfakes based on generative adversarial networks, pose a risk to the epistemic basis of journalism by bringing in the perceived authenticity of visual evidence to doubt (Vaccari and Chadwick, 2020). The first deepfakes were low-quality and easy to spot, but the current systems are photoreal and can pass as video and audio to human viewers and most of the detecting algorithms. Historical journalism has been used to the visual evidence as verification through the use of photographs to prove events, videos to record speeches and audio to record confessions. This state of evidence fails when any media can be convincingly made up.

News organizations have reacted to this by creating detection mechanisms and verification processes. To verify the provenance of media, the New York Times, BBC, and Reuters joined forces with academic scholars in developing the Content Authenticity Initiative, which authenticates media with the help of cryptographic watermarking (Farid, 2019). There were Microsoft and Facebook deepfake detection challenges which announced prizes, speeding up the progress of the algorithm. However, this is a cat-and-mouse game where generative systems get better and better faster than the detectors, and nothing has a long-term solution (Chesney & Citron, 2019). The more profound one is sociological: when people are informed of the possibility of fabrication, they can dismiss authentic evidence as such, leading to what Wardle & Derakhshan (2017) refer to as information disorder, in which citizens can no longer be sure of what is truth and what is fake.

The opportunities of conversational AI and voice-activated news platforms are new and have unpredictable democratic possibilities. Amazon Alexa, Google Assistant, and Apple's Siri are becoming increasingly engaging as news interfaces, as millions of users are briefed on voice every day (Howell, 2018). There are accessibility benefits of these platforms, namely that they are accessible by people with visual impairment and allow them to consume news even when performing other tasks, such as commuting or cooking; yet, these platforms present a specific concern regarding the diversity of sources and their transparency. Voice assistants usually locate individual sources to answer questions as opposed to a variety of possible choices, which makes the algorithmic selection more significant. There is also immense secrecy in editorial decision-making in that users seldom understand what news source they are being briefed on, and why that source was chosen (Gillespie, 2014).

In addition, conversational interfaces bring in new interaction patterns that transform the way news is consumed. In traditional journalism, it is assumed that there is a conscious interaction between the reader and the information-seeker. Voice assistants facilitate passive consumption such that news is delivered without requesting it and according to factors of algorithmic prediction of interest. This movement of the pull toward the push transforms the democratic role: citizens are no longer actively informed, but they are updated in an algorithmic manner. Questions have been raised on whether passive consumption creates the critical engagement that democratic citizenship demands, as its benefits are obvious (Hindman, 2018).

Our vision of responsible AI integration in journalism is given in Fig. 3, which is a result of implementation pattern and democratic analysis.

Fig. 3 realizes the abstract democratic commitments in the terms of concrete organizational practices. The framework does not support technological determinism (AI will inevitably change journalism in specific ways) or social constructivism (technology is endlessly flexible to social decisions) instead favoring the understanding that AI systems have affordances and constraints which have to be actively addressed through institutional design. The feedback loops recognize that responsible integration is not an event but a continuous process which needs adjustment as the technologies and social contexts change.

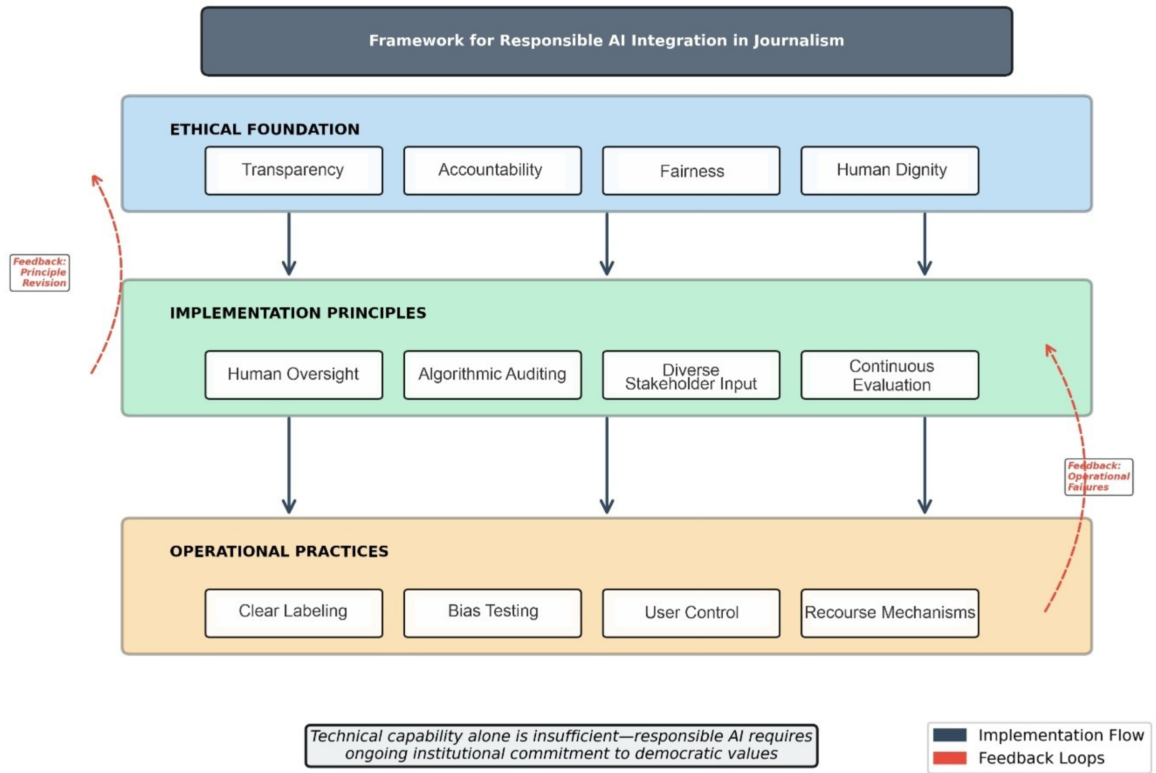


Fig. 3: RAI model of integration into journalism. The framework operates at three levels (1) Ethical Foundations (transparency, accountability, fairness, human dignity); (2) Implementation Principles (human oversight, algorithmic auditing, diverse stakeholder input, continuous evaluation); (3) Operational Practices (clear labeling, bias testing, user control, recourse mechanisms). They have arrows indicating that there exists feedback loop where operation failure assists in principle revision and reflections of ethics. The framework underlines that the technical capability is insufficient, but responsible AI should possess further institutional support of the notion of democracy.

3.5 Synthesis: Balancing Innovation and Democratic Values

The analyzed evidence demonstrates that some underlying tensions which cannot be easily solved are present. At the same time and in different levels and periods the artificial intelligence forms and threatens the democracy of journalism. Efficiency that may be achieved through automation allows newsrooms to cover more events with less labor and this would improve accountability due to more coverage. Nevertheless, it is the same systems that introduce biases that are discriminating against some communities and subjects more systematically and potentially reduce the degree of accountability of already underrepresented individuals.

The concurrent occurrence of these contradictory implications necessitates not technology optimism and technology pessimism but rather structures. Whether AI is detrimental or beneficial to democratic journalism is not the question, but the fact that some implementations, governance structures and social conditions produce some ratios of good and bad. This landscape has three principal tensions in which it is organized:

To begin with, AI applications are full of efficiency versus quality trade-offs. Automated content generation is cheaper and quicker in production than human journalists and less analytical and contextual. The system of algorithmic curation analyzes more content and is personalized better than human editors but with less civic consideration and minority interests. Data journalism is able to process and detect more patterns than a traditional investigation, at least in part, because it can process larger datasets and analyze them, and it is likely to succumb to the fallacy of stating correlation as causation and simplifying a complex social problem into a statistical correlation. Both technologies provide scalability and efficiency that jeopardizes quality as a result of standardization and simplification.

Second, the tensions of innovation versus accountability arise due to the speed and the obscurity of AI. Machine learning systems work using statistical patterns that are hard to interpret using a mode of interpretation that can be understood by a journalist or audience. In situations where editorial decisions are carried out by automated systems, the conventional tools of accountability, editorial control, peer review and critical public opinion are hard pressed to evaluate decisions that are rationale in high-dimensional parameter space. This obscurity is contrary to the democratic role of journalism, which should rely on justifying its choices by transparent reasoning that can be assessed by the audience. The rate of innovation worsens the issue of accountability since newsrooms implement systems, the long-term impacts of which are not quite clear.

Third, individualism versus integrity trade-offs are more profound democratic conflicts. News can be made more topical and easier to access with the help of algorithmic personalization, which can result in the growth of engagement and comprehension. However, democracy needs unity and knowledge that is unified, that personalization endangers. The citizens require content that talks about personal issues and content that informs them about the social issues that are affecting communities that the citizens are not part of. Algorithms that are optimized to effectively engage individuals can challenge the public-ness that is fundamental to publics and divide society into different information realities, where there is little understanding of each other.

These tensions are not bugs that can be resolved by making the design better but structural characteristics of AI implementation in the journalism profession. They are based on the fundamental features of machine learning (statistical instead of causal reasoning, optimization towards given objectives, pattern recognition using past information) and the democratic aspect of journalism (meeting the needs of individuals and the collective betterment, maintaining commercial sustainability and social responsibility, balancing speed with accuracy). Effective ways to work with AI in journalism will be possible only by recognizing these tensions and establishing organizational structures to negotiate around them instead of assuming that technical solutions can avoid tough trade-offsn

4.0 Conclusions

The investigation of the transformative power of AI concerning the sphere of digital journalism discloses a far more complex image than utopian and dystopian accounts would represent. Those arguments demonstrate that AI, such as the automated content creation, algorithmic curation, and data-driven investigation, actually change the essence of news development, dissemination and intake with some far-reaching implications on the democratic society. These technologies empower journalism by making it more efficient, analytically powerful, scaled and at the same time disturbing biases, obscure and fractured. In another way, the democratic implication is also rather counterpropositional: AI makes it easier to conduct fact-checking and investigative journalism and decreases the effectiveness of discourse, at least in terms of quality, and disintegrates publics. These tensions are understood with the aid of the present research by not only mapping the applications of AI in journalism but also assessing their multidimensional impacts on democracy and recommending forms of responsible incorporation. Wholesale dismissal and blind acceptance of AI are not where the future is heading but rather the institutional designs that are proactively trying to find a balance between innovation and citizen accountability. Transparency, algorithmic auditing, human interaction should be invested by the news producers; explainability and fairness should be focused upon by the technology creators, performance should be given by the policymakers and both technical and ethical literacy should be developed by the journalism education. The research in future should aim to find longitudinal research of tracking the evolving impact of AI, cross-cultural studies of the impact of regulatory and cultural environment on the final product and investigate the latest technologies like generative AI the impact of which have not been well studied to date. Only in such a critical interaction can we be sure that the AI is a servant of the journalism and not its poisoner.

5.0 References

Ananny, M., & Crawford, K. (2018). Seeing without knowing: Limitations of the transparency ideal and its application to algorithmic accountability. *New Media & Society, 20*(3), 973–989. https://doi.org/10.1177/1461444816676645

Angwin, J., & Tobin, A. (2021). Facebook enabled advertisers to reach 'Jew haters'. *The Markup*. https://doi.org/10.21428/5b0c15e3.c9ef3b9f

Angwin, J., Larson, J., Mattu, S., & Kirchner, L. (2016). Machine bias. *ProPublica, 23*, 2016. https://doi.org/10.1145/2935876.2935878

Babakar, M., & Moy, W. (2016). *The state of automated factchecking*. Full Fact. https://doi.org/10.17605/OSF.IO/9FC3T

Bakshy, E., Messing, S., & Adamic, L. A. (2015). Exposure to ideologically diverse news and opinion on Facebook. *Science, 348*(6239), 1130–1132. https://doi.org/10.1126/science.aaa1160

Beam, M. A. (2014). Automating the news: How personalized news recommender system design choices impact news reception. *Communication Research, 41*(8), 1019–1041. https://doi.org/10.1177/0093650213497979

Beckett, C. (2019). *New powers, new responsibilities: A global survey of journalism and artificial intelligence*. Polis, LSE. https://doi.org/10.21953/lse.zpj64bcxvxne

Bell, E., & Owen, T. (2017). *The platform press: How Silicon Valley reengineered journalism*. Tow Center for Digital Journalism. https://doi.org/10.7916/D8 R216ZZ

Benkler, Y., Faris, R., & Roberts, H. (2018). *Network propaganda: Manipulation, disinformation, and radicalization in American politics*. Oxford University Press. https://doi.org/10.1093/oso/9780190923624.001.0001

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., ... Amodei, D. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems, 33*, 1877–1901. https://doi.org/10.48550/arXiv.2005.14165

Bucher, T. (2012). Want to be on the top? Algorithmic power and the threat of invisibility on Facebook. *New Media & Society, 14*(7), 1164–1180. https://doi.org/10.1177/1461444812440159

Carlson, M. (2015). The robotic reporter: Automated journalism and the redefinition of labor, compositional forms, and journalistic authority. *Digital Journalism, 3*(3), 416–431. https://doi.org/10.1080/21670811.2014.976412

Carlson, M. (2018). Facebook in the news: Social media, journalism, and public responsibility following the 2016 trending topics controversy. *Digital Journalism, 6*(1), 4–20. https://doi.org/10.1080/21670811.2017.1298044

Chen, Y., Conroy, N. J., & Rubin, V. L. (2015). Misleading online content: Recognizing clickbait as false news. *Proceedings of the 2015 ACM Workshop on Multimodal Deception Detection*, 15–19. https://doi.org/10.1145/2823465.2823467

Chesney, R., & Citron, D. (2019). Deep fakes: A looming challenge for privacy, democracy, and national security. *California Law Review, 107*, 1753–1820. https://doi.org/10.15779/Z38RV0D15J

Christians, C. G., Glasser, T. L., McQuail, D., Nordenstreng, K., & White, R. A. (2009). *Normative theories of the media: Journalism in democratic societies*. University of Illinois Press. https://doi.org/10.5406/illinois/9780252034008.001.0001

Clerwall, C. (2014). Enter the robot journalist: Users' perceptions of automated content. *Journalism Practice, 8*(5), 519–531. https://doi.org/10.1080/17512786.2014.883116

Coddington, M. (2015). Clarifying journalism's quantitative turn: A typology for evaluating data journalism, computational journalism, and computer-assisted reporting. *Digital Journalism, 3*(3), 331–348. https://doi.org/10.1080/21670811.2014.976400

DeVito, M. A. (2017). From editors to algorithms: A values-based approach to understanding story selection in the Facebook news feed. *Digital Journalism, 5*(6), 753–773. https://doi.org/10.1080/21670811.2016.1178592

Diakopoulos, N. (2019). *Automating the news: How algorithms are rewriting the media*. Harvard University Press. https://doi.org/10.4159/9780674239302

Diakopoulos, N., & Koliska, M. (2017). Algorithmic transparency in the news media. *Digital Journalism, 5*(7), 809–828. https://doi.org/10.1080/21670811.2016.1208053

Díaz-Struck, E. (2017). How artificial intelligence helped us find patterns in the Panama Papers. *ICIJ Blog*. https://doi.org/10.7916/D8N014W6

Fanta, A. (2017). *Putting Europe's robots on the map: Automated journalism in news agencies*. Reuters Institute Fellowship Paper. https://doi.org/10.1080/216708 11.2017.1279097

Farid, H. (2019). Fake photos. *IEEE Signal Processing Magazine, 36*(2), 40–45. https://doi.org/10.1109/MSP.2018.2876837

Flaxman, S., Goel, S., & Rao, J. M. (2016). Filter bubbles, echo chambers, and online news consumption. *Public Opinion Quarterly, 80*(S1), 298–320. https://doi.org /10.1093/poq/nfw006

Flew, T., Spurgeon, C., Daniel, A., & Swift, A. (2012). The promise of computational journalism. *Journalism Practice, 6*(2), 157–171. https://doi.org/10.1080/17512786 .2011.616655

Gangadharan, S. P. (2017). The downside of digital inclusion: Expectations and experiences of privacy and surveillance among marginal internet users. *New Media & Society, 19*(4), 597–615. https:// doi.org/10.1177/1461444815614053

Gilardi, F., Di Lorenzo, S., Ezzaini, J., Santa, B., Streiff, B., Zurfluh, E., & Hoes, E. (2024). Willingness to read AI-generated news is not driven by their perceived quality. *arXiv*. https://doi.org/10.48550/arXiv.2409.03500

Gillespie, T. (2014). The relevance of algorithms. In T. Gillespie, P. Boczkowski, & K. Foot (Eds.), *Media technologies: Essays on communication, materiality, and society* (pp. 167–194). MIT Press. https:// doi.org/10.7551/mitpress/9780262525374.003.0009

Graefe, A. (2016). *Guide to automated journalism*. Tow Center for Digital Journalism. https://doi.org/10.7916/D80 R9XH3

Graefe, A., Haim, M., Haarmann, B., & Brosius, H. B. (2018). Readers' perception of computer-generated news: Credibility, expertise, and readability. *Journalism, 19*(5), 595–610. https://doi.org/10.1177/1464884916641269

Graves, L. (2018). *Understanding the promise and limits of automated fact-checking*. Reuters Institute Factsheet. https://doi.org/10.1080/21670811.2016.1266804

Greenslade, R. (2018). The end of local news as we know it. *The Guardian*. https://doi.org/10.1080/17512786.2018.1467883

Habermas, J. (1989). *The structural transformation of the public sphere: An inquiry into a category of bourgeois society*. MIT Press. https://doi.org/10.7551/mitpress/9780262561679.001.0001

Hansen, M., Roca-Sales, M., Keegan, J. M., & King, G. (2017). *Artificial intelligence: Practice and implications for journalism*. Tow Center for Digital Journalism. https://doi.org/10.7916/D8X92PRD

Hassan, N., Arslan, F., Li, C., & Tremayne, M. (2017). Toward automated factchecking: Detecting check-worthy factual claims by ClaimBuster. *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 1803–1812. https://doi.org/10.1145/3097983.3098131

Hassan, N., Li, C., & Tremayne, M. (2015). Detecting check-worthy factual claims in presidential debates. *Proceedings of the 24th ACM International Conference on Information and Knowledge Management*, 1835–1838. https://doi.org/10.1145/2806416.2806652

Hermida, A., Fletcher, F., Korell, D., & Logan, D. (2012). Share, like, recommend: Decoding the social media news consumer. *Journalism Studies, 13*(5–6), 815–824. https://doi.org/10.1080/1461670X.2012.664430

Hermida, A., & Young, M. L. (2019). *Data journalism and the regeneration of news*. Routledge. https://doi.org/10.4324/9781315163895

Hindman, M. (2018). *The internet trap: How the digital economy builds monopolies and undermines democracy*. Princeton University Press. https://doi.org/10.1515/9781400890521

Howell, L. (2018). Voice-activated assistants and the news. *Reuters Institute Digital News Report*. https://doi.org/10.60625/risj-qz68-7m91

Kilgo, D. K., Harlow, S., García-Perdomo, V., & Salaverría, R. (2018). A new frontier in journalism? The performance and professionalization of online and offline protest coverage. *Journalism Studies, 19*(10), 1355–1375. https://doi.org/10.1080/1461670X.2016.1266910

Latar, N. L. (2015). The robot journalist in the age of social physics: The end of human journalism? In G. Einav (Ed.), *The new world of transitioned media* (pp. 65–80). Springer. https://doi.org/10.1007/978-3-319-09009-26

Napoli, P. M. (2014). Automated media: An institutional theory perspective on algorithmic media production and consumption. *Communication Theory, 24*(3), 340–360. https://doi.org/10.1111/comt.12039

Nechushtai, E. (2018). Could digital platforms capture the media through infrastructure? *Journalism, 19*(8), 1043–1058. https://doi.org/10.1177/1464884917725163

Nechushtai, E., & Lewis, S. C. (2019). What kind of news gatekeepers do we want machines to be? *Computers in Human Behavior, 90*, 298–307. https://doi.org/10.1016/j.chb.2018.07.043

Newman, N., Fletcher, R., Schulz, A., Andı, S., & Nielsen, R. K. (2020). *Reuters Institute Digital News Report 2020*. Reuters Institute for the Study of Journalism. https://doi.org/10.60625/risj-4h0x-1m83

Nielsen, R. K. (2016). The business of news. In T. Witschge, C. W. Anderson, D. Domingo, & A. Hermida (Eds.), *The SAGE handbook of digital journalism* (pp. 51–67). SAGE. https://doi.org/10.4135/9781473957909.n4

Nielsen, R. K., & Ganter, S. A. (2018). Dealing with digital intermediaries: A case study of the relations between publishers and platforms. *New Media & Society, 20*(4), 1600–1617. https://doi.org/10.1177/1461444817701318

Noble, S. U. (2018). *Algorithms of oppression: How search engines reinforce racism*. NYU Press. https://doi.org/10.18574/nyu/9781479833641.001.0001

O'Neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Crown. https://doi.org/10.17104/9783406709333

Pariser, E. (2011). *The filter bubble: What the internet is hiding from you*. Penguin Press. https://doi.org/10.3139/9783446431164

Pasquale, F. (2015). *The black box society: The secret algorithms that control money and information*. Harvard University Press. https://doi.org/10.41n59/harvard.9780674736061

Pavlik, J. V. (2023). Collaborating with ChatGPT: Considering the implications of generative artificial intelligence for journalism and media education. *Journalism & Mass Communication Educator, 78*, 84–93. https://doi.org/10.1177/10776958221149577

Petticrew, M., & Roberts, H. (2006). *Systematic reviews in the social sciences: A practical guide*. Blackwell. https://doi.org/10.1002/9780470754887

Royal, C. (2020). The journalist as programmer: A case study of *The New York Times* interactive news technology department. *Journalism Practice, 14*(10), 1248–1265. https://doi.org/10.1080/17512786.2019.1698974

Shin, D., & Park, Y. J. (2019). Role of fairness, accountability, and transparency in algorithmic affordance. *Computers in Human Behavior, 98*, 277–284. https://doi.org/10.1016/j.chb.2019.04.019

Sunstein, C. R. (2017). *#Republic: Divided democracy in the age of social media*. Princeton University Press. https://doi.org/10.1515/9781400884711

Thorson, K., & Wells, C. (2016). Curated flows: A framework for mapping media exposure in the digital age. *Communication Theory, 26*(3), 309–328. https://doi.org/10.1111/comt.12087

Thurman, N., & Schifferes, S. (2012). The future of personalization at news websites: Lessons from a longitudinal study. *Journalism Studies, 13*(5–6), 775–790. https://doi.org/10.1080/1461670X.2012.664341

Thurman, N., Moeller, J., Helberger, N., & Trilling, D. (2019). My friends, editors, algorithms, and I: Examining audience attitudes to news selection. *Digital Journalism, 7*(4), 447–469. https://doi.org/10.1080/21670811.2018.1493936

Tobin, A., Varner, M., & Angwin, J. (2019). Facebook's uneven enforcement of hate speech rules allows vile posts to stay up. *ProPublica*. https://doi.org/10.21428/5b0c15e3.d946d0ef

Usher, N. (2016). *Interactive journalism: Hackers, data, and code*. University of Illinois Press. https://doi.org/10.5406/illinois/9780252040009.001.0001

Vaccari, C., & Chadwick, A. (2020). Deepfakes and disinformation: Exploring the impact of synthetic political video on deception, uncertainty, and trust in news. *Social Media + Society, 6*(1). https:

//doi.org/10.1177/2056305120903408

van der Kaa, H., & Krahmer, E. (2014). Journalist versus news consumer: The perceived credibility of machine-written news. *Proceedings of the Computation + Journalism Conference*. https://doi.org/10.1145/2755996.2756006

Vos, T. P., & Finneman, T. (2017). The early historical construction of journalism's gatekeeping role. *Journalism, 18*(3), 265–280. https://doi.org/10.1177/1464884916636126

Waddell, T. F. (2019). Can an algorithm reduce the perceived bias of news? *Journalism & Mass Communication Quarterly, 96*(1), 82–100. https://doi.org/10.1177/1077699018815891

Wardle, C., & Derakhshan, H. (2017). *Information disorder: Toward an interdisciplinary framework for research and policy making*. Council of Europe. https://doi.org/10.58944/vxzh8493

Young, M. L., & Hermida, A. (2015). From Mr. and Mrs. Outlier to central tendencies: Computational journalism and crime reporting at the *Los Angeles Times*. *Digital Journalism, 3*(3), 381–397. https://doi.org/10.1080/21670811.2014.976409

Zamith, R. (2018). Quantified audiences in news production: A synthesis and research agenda. *Digital Journalism, 6*(4), 418–435. https://doi.org/10.1080/21670811.2018.1444999

Declaration

Funding sources

No funding

Competing Financial Interests Statement:

There are no competing financial interests in this research work.

Ethical considerations

Not applicable

Data availability

The microcontroller source code and any other information can be obtained from the corresponding author via email.

Authors' Contribution

The author carried out all components of the work