AI Is Here To Stay: Misinformation and Human-Centric Models Between Risks and Opportunities

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1 INTRODUCTION

Artificial intelligence has fascinated the scientific community for almost a century, spurring famous research papers such as Alan Turing's *"Computing Machinery and Intelligence"* in 1950 [50], which introduced the *imitation game*. The idea, trivialized, is that any machine capable of fooling a person into thinking it's speaking to a human can be considered sentient. For seventy-three years the game remained unbeaten, until OpenAI's ChatGPT-4 ultimately succeeded in 2023 [2]. The model, simulating AGI capabilities [5], is one of the last iterations of the Generative Pre-Training LLMs[1] pioneered by OpenAI in 2018 (at the moment of writing the latest available is GPT-5.2) [35], which closely followed the first breakthrough towards human-like agents: *"Attention Is All You Need"* [52] is a 2017 landmark research paper authored by eight Google researchers that introduced the *transformer* architecture, considered the backbone of all modern LLMs and the main contributor of the AI boom [25].

Computer scientists are not the only ones engrossed in the topic: philosophers involved themselves too, most notably Jhon Searle and his 1980s' *chinese room* thought experiment, which directly challenged Turing's ideas and refuted the possibility of true machine intelligence [48], and even the general public showed great interest once AIs became smart enough: ChatGPT reached one million users in just five days [27], an astonishing feat when compared to other technologies such as personal computers, which needed almost ten years to reach the same milestone [36].

Despite all of the above, the field of artificial intelligence comes with its fair share of problems and controversies: due to their inherent design, LLMs pose significant privacy risks as sensitive information is collected and used to create and fine-tune the models themselves [15], and their black-box nature makes it difficult to understand and predict their behavior [55]. Moreover, they are often trained on pirated material, like books [37] or art [26], igniting protests in many creative communities, such as hollywood writers [28] or video game actors [34]. It follows that artificial intelligence technologies should be handled carefully, without hindering their development while limiting the damages they can cause to society and individuals.

[1]Large Language Models (LLMs) are trained with supervised machine learning on vast amount of textual data, and are designed for natural language processing tasks, especially language generation [3, 4]

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This survey paper aims to present the current state of research on ethical and human-centric artificial intelligence, exploring how models and humans can influence each other and their environment. Section 2 showcases generation and detection of fake-news, section 3 recognition and simulation of human behaviour, as well as how to influence it. Section 4 concerns itself with biases and tendencies of the models themselves, and lastly section 5 explores ways to develop ethical LLMs that can positively impact individuals and society.

2 AI FOR FAKE NEWS GENERATION AND DETECTION

Fake news have rapidly become a significant concern in the digital age, thanks to their virality and potential damages. They spread faster and generate more engagement than truthful information [20, 49], and can influence public opinion, manipulate elections and pose a threat to public health. For example, the World Economic forum has identified the proliferation of false content as the leading short-term global risk in 2025 [6], and a BBC investigation found Russian-funded fake news networks aiming to disrupt european elections [22]. Moreover, fake news on health can cause psychological disorders and panic, fear, depression, and fatigue [38], making the World Health Organization call for development of international fact-checking organizations to combat this phenomenon [30].

Adding to the problem, the recent advancements in generative artificial intelligence have made it significantly easier to propagate misinformation through the web: generated content is increasingly indistinguishable from human-written text, sometimes even perceived as more credible [21], citing true evidence to support false claims [13], and inducing the illusion of majority opinion thanks to the sheer volume of information produced [10].

That being said, not all findings are entirely negative: Drolsbach and Pröllochs [12] shift their focus from potential societal consequences to real-world prevalence, conducting a large-scale analysis on the platform *X*. They analyzed a dataset comprising 91.452 misleading posts, both human and AI-generated, flagged trough X's *Community Notes* platform [2]. Their findings reveal that generated fake news are often centered on entertaining content rather than controversial or political subjects, and tends to exhibit a more positive sentiment than conventional forms of misinformation. Unfortunately, it is also significantly more likely to go viral.

Lastly, AI agents can produce more than just text: they can create realistic images, videos and sounds, allowing them to make digital copies of real or fictional people, known as deepfakes. In March 2019, such a technology has been used to trick a UK-based energy firm's CEO into transferring $243.000 to a malicious party, disguised as an entirely AI-generated executive from their parent company [14]. Deepfakes also increase the amount of conspiratorial videos on the internet, and they are especially vicious when targeting children, whose worldviews are easily swayed by deceptive, highly photorealistic content [53].

It follows that detecting and mitigating fake news is crucial. From the foundational work by Devlin et al. on *BERT* in 2018 [9], which revolutionized natural language processing trough deep bidirectional transformers, to the application of said transformers in identifying automatically generated headlines [23]; the landscape of automated fake news detection has significantly expanded. Vijjali et al. [54] developed a two-stage transformer-based model for detecting COVID-19 related misinformation, combining fact-checking with textual entailment to verify claims. Their model performs significantly better than other baseline NLP approaches (table 1).

Jwa et al. [19] propose an improved *exBAKE* model that leverages pre-training on a BERT model to accurately understand and assess articles' authenticity. They only analyzed the relationship between headlines body. Results can be seen in table 2.

[2] Community Notes, formerly known as Birdwatch, is community-drive content moderation program on X (formerly Twitter), where contributors can add context such as fact-checks under a post, image or video. GitHub repository: https://github.com/twitter/communitynotes

Table 1. Precision metrics for two-stage transformer model for COVID-19 fake news detection, Vijjali et al [54]

Models	MRR	Recall@10	Accuracy
TF-IDF	0.477	0.635	0.525
GloVe	0.182	0.410	0.579
MobileBERT	0.561	0.735	0.710
BERT	0.632	0.795	0.810
ALBERT	0.582	0.675	0.825
BERT+ALBERT	0.632	0.795	0.855

Table 2. Precision metrics for exBAKE transformer model on fake news recognition, Jwa et al. [19]

Models	F1	AGR	DSG	DSC	UNR
Majority vote	0.210	0.000	0.000	0.000	0.839
BERT	0.656	0.651	0.145	**0.839**	0.989
BAKE	0.734	0.667	0.463	0.822	0.986
exBAKE	**0.746**	**0.684**	**0.501**	0.813	0.988
Upper bound	0.754	0.588	0.667	0.765	0.997

Schütz et al. [46] experimented on *FakeNewsNet* dataset with *XLNet*, BERT, *RoBERTa*, *DistilBERT*, and *ALBERT* and various combinations of hyperparameters. The evaluation shows that already short texts are enough to attain 85% accuracy on the test set. Using the body text and a concatenation of both reach up to 87% accuracy. Lastly, on the matter of deepfakes, Bansal et al. [1] use *Convolutional Neural Networks* (CNN) and *Deep Convolutional Generative Adversarial Networks* (GAN) to detect them with high accuracy, as shown in figure 1.

These were just a small selection of the many research works in the field of AI-aided fake news generation and detection, which while being extremely relevant and proliferous, are but a fraction of the many potential uses for these technologies.

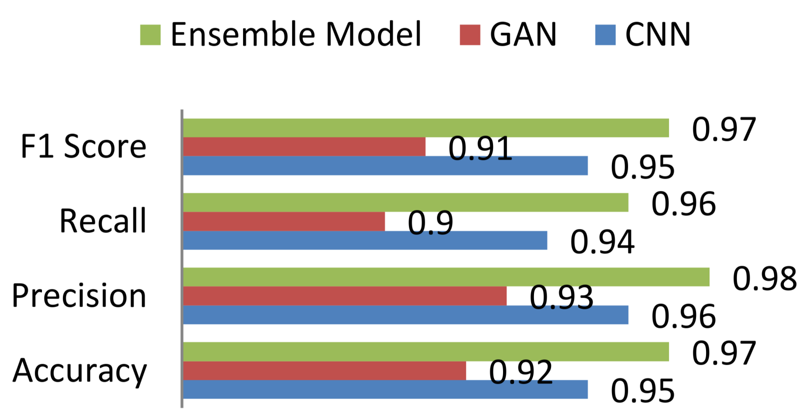

Fig. 1. Transformer models scores on deepfakes detection, Bansal et al. [1]

3 AI FOR UNDERSTANDING AND INFLUENCING HUMAN BEHAVIOUR

Today's society is already fully dependent on technology: from the banking system, to traffic monitoring and management or public health databases, IT systems have become essential. Individuals are in the same situation: virtually everyone in global north under the age of 65 possess a smartphone and use it daily [17]. It follows that artificial intelligence will become an integral part of our personal and professional lives, therefore modeling it to mimic our behaviors could aid in its usefulness and understanding. There are already evidences that humans can exploit it to acquire better comprehension of a phenomenon [45], and it can also enhance creativity in heterogeneous groups [51]. Moreover, LLMs represents a significant methodological shift in computational communication science, enabling a more flexible, more nuanced, but also less controllable exploration of social theories that have historically been difficult to reduce to simple mathematical formalisms [31]. Overall, AI promises to be a good fit for understanding, modeling and replicating human behaviour.

For these very purposes, Dos Santos Melicio et al. [11] propose a three-phase AI framework (figure 2) that analyzes verbal and non-verbal social cues. First, deep learning methods are employed to extract relevant information from the environment. Then, the episode detection phase uses extracted features to identify key moments, or episodes, which are then classified in the activity interpretation phase. Overall, the system can recognize verbal hints with 87% accuracy and non-verbal ones with 89% accuracy, with zero false positives. The system was tested in an automated assessment of communicative skills of children with Autism Spectrum Disorder (ASD), a challenging context where social cues may be less noticeable or outright absent.

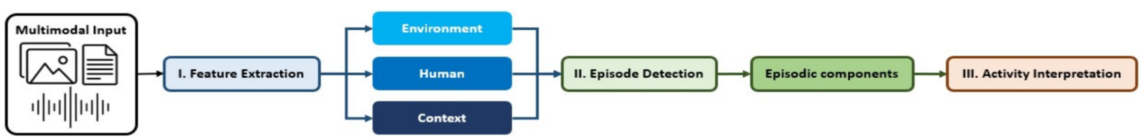

Fig. 2. Composite AI framework: Deep Learning methods extract features which are then combined with rule-based systems for detecting key episodes, and then classifiers are used to interpret activities happening in the scene. Dos Santos Melicio et al. [11]

Another possible use of such capabilities is hate speech detection: the rise of social networks and online platforms translated into a surge in hate speech across geographical and cultural boundaries. In recent studies, approximately 30% of the adolescents surveyed reported experiencing cyberbullying at some point in their lives. Furthermore, around 13% indicated that they had been cyberbullied within the 30 days before the survey [32].

To address these challenges, Chapagain et al. [7] evaluate different LLMs (BART, ELECTRA, BERT, RoBERTa, and GPT-2) on the extensive *MetaHate* dataset [33]. ELECTRA achieved the highest F1 score (table 3), outperforming all other baselines in hate speech classification

These technologies can also be used to influence people opinions. Huq et al. [18] tested this with AI-assisted messaging in an online chat platform. 557 Participants were randomly assigned to sessions of six to fifteen people, further subdivided into groups of two to four. They discussed politically controversial topic selected to maximize opinion diversity within each three-minutes session, at the end of which they chose whether to remain in their current group, join another, or create a new one. Some of them received suggestions from large language models, either personalized to their own opinion (*"individuals"*) or more similar to the group's (*"relational"*).

Table 3. Performance of classifiers on MetaHate, Chapagain et al [7]

Models	F1 Score	Accuracy
SVM	0.8380	0.8466
CNN	0.8422	0.8612
BERT	0.8809	0.8879
GPT2	0.6504	0.6152
T5	0.8707	0.8625
DeBERTa	0.8808	0.8746
Longformer	0.8845	0.8785
RoBERTa	0.8908	0.8858
XLNet	0.8917	0.8870
BART	0.8928	0.8886
DistilBERT	0.8940	0.8905
ELECTRA	**0.8980**	**0.8946**

The results show that individual assistance amplified communication volume yet increased separation between groups, while relational assistance fostered more receptive conversations and produced more heterogeneous, cross-cutting group configurations, highlighting both the dangers and the possibilities of employing artificial agents in such a fashion.

Similar conclusions can be seen in other research results: Hohenstein et al. [16] highlights how AI response suggestion systems change how people interact with and perceive one another in both pro-social and anti-social ways. Moreover, Noy et al. [29] shows that people tend to send more messages when suggestions are available, but rarely edit them, suggesting partial delegation of expressive effort.

Overall, AI tools seem capable of reducing harmful online behaviors, but can potentially be extremely disruptive due to their capability of influencing people's opinions and reducing autonomous behaviour.

4 AI OWN BIASES AND INFLUENCEABILITY

Since artificial agents are trained on mostly human-generated data, they learn human biases and tendencies themselves, developing both historical and political preferences in the textual content they generate [39, 41, 42]. They tend to exhibit social sycophancy, by agreeing with and flattering the user at the cost of correctness [8], and they are easily influenced by small changes in prompt wording [44, 47]. This can raise ethical concerns as biased AIs lead to discrimination or exclusion of marginalized groups. [40].

Rozado, in the context of US politics, measured the political bias of many popular large language models [43]. First, they calculated the similarity between AI-generated text and public speeches from Congress representatives (both Democrat and Republican). Then, they used an LLM to annotate as left- or right-leaning AI-generated policy recommendations. Consequently, they did a sentiment analysis on AI-generated comments about american public figures, such as legislators or journalists (figure 3), and lastly they administered three different political orientation tests to the various LLMs. The results show substantial evidence that the models are biased and left-leaning. Table 4 shows the three most and three least biased LLMs among those tested.

As previously stated, AIs can be easily influenceable. Mehdizadeh and Hilbert [24] test such a theory by subjecting LLMs to peer-pressure. The models are immersed into fictitious social networks (figure 4), and each agent periodically

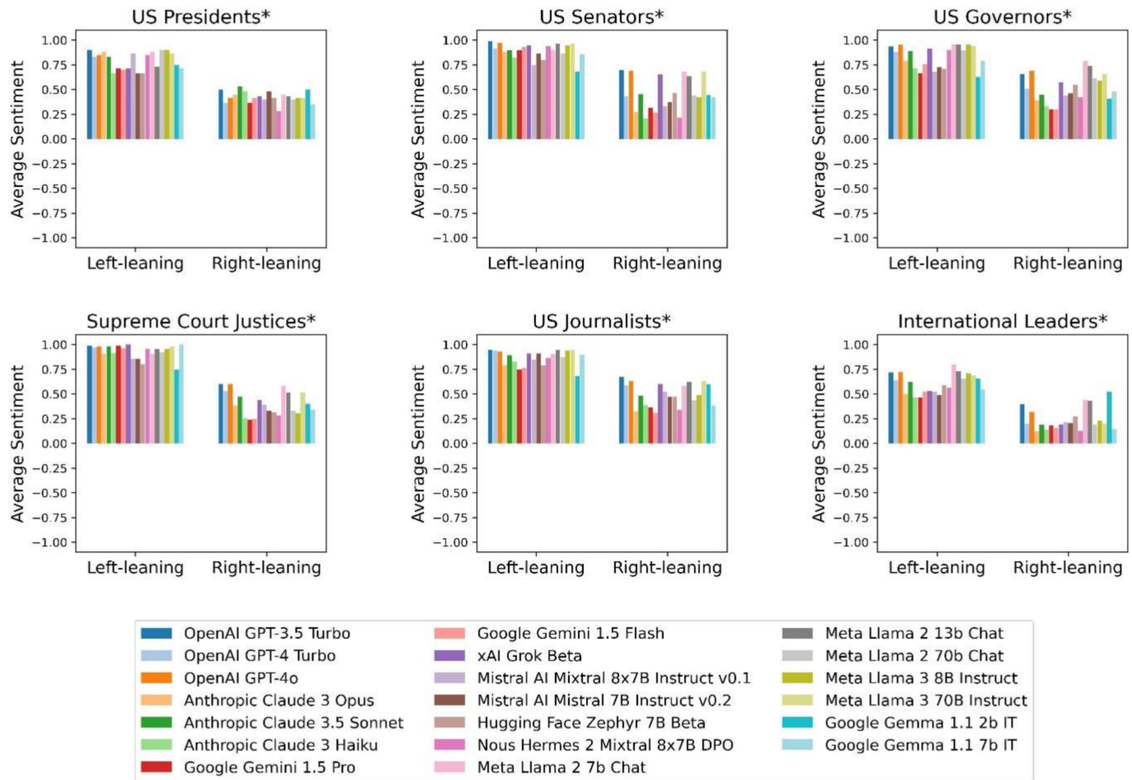

Fig. 3. Average sentiment (negative: -1, neutral: 0, positive: 1) towards ideologically aligned public figures in conversational LLMs' generated texts. Statistically significant two-sample t-tests at the 0.01 threshold are indicated with an asterisk. Rozado [43]

Table 4. Ranking of political bias in conversational LLMs sorted in ascending order from least politically biased to most. Rozado [43]

Rank	**Model**
1	Google Gemma 1.1 2b IT
2	xAI Grok Beta
3	Mistral AI Mistral 7B Instruct v0.2
...	...
18	Nous Hermes 2 Mixtral 8x7B DPO
19	Google Gemini 1.5 Pro
20	Google Gemini 1.5 Flash

receives a natural language prompt summarizing the opinions of its immediate neighbors. It then decides whether to update its opinions or not. The flowchart of the simulation can be seen at figure 5.

Overall, the study highlights two main results: agents' malleability depends on the model (*Gemini 1.5 Flash* requires over 70% peer disagreement to flip, whereas *ChatGPT-4o-mini* shifts with a dissenting minority), and different cognitive orientations respond differently to outside stimuli. For *values* and *opinions*, agents show a strong resistance to abandoning a "Yes" stance, making them robust once affirmed , whereas for *attitudes* and *intentions* the greatest challenge is overcoming a negative "No". On the other hand, *beliefs* display a near-perfect symmetry.

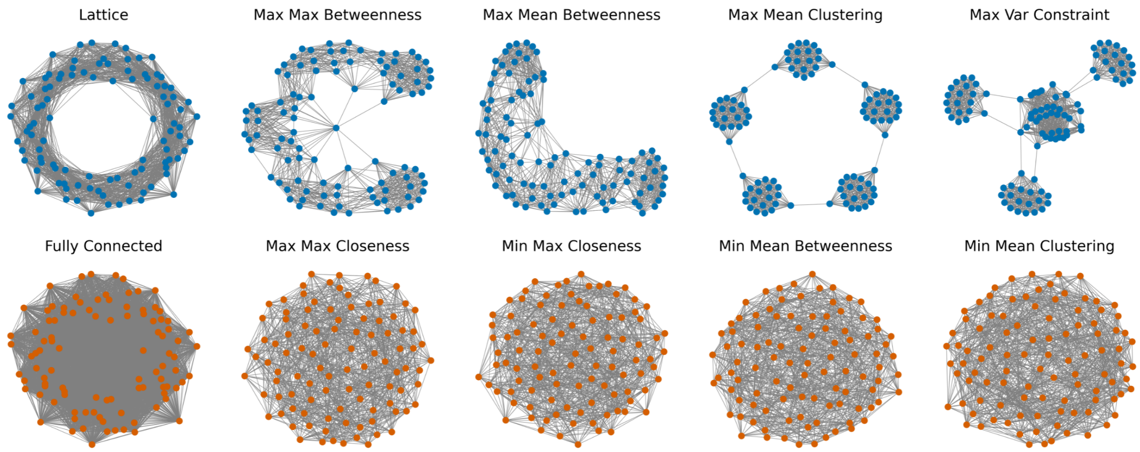

Fig. 4. The then 100-nodes networks used in the study. Mehdizadeh and Hilbert [24].

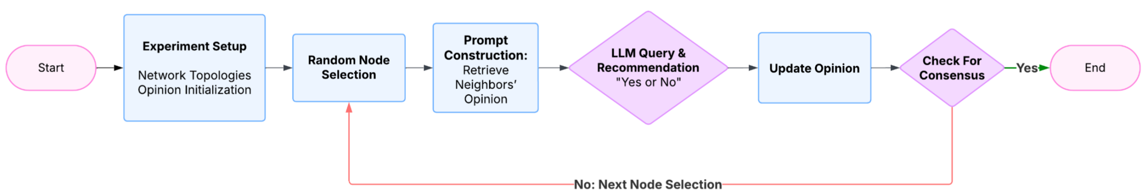

Fig. 5. Flowchart of the simulation procedure in the LLM-driven network model. The process continues asynchronously across the network until a specified number of steps or convergence criterion is met. The setup measures how local peer influence, mediated through LLM interpretation, shapes the emergent collective opinion. Mehdizadeh and Hilbert [24]

In conclusion, the literature offers empirical proof that artificial agents inherit biases from their training data and are influenced by external stimuli. This, combined with their ability to manipulate humans' opinions (section 3), raises ethical concerns that must be addressed.

5 ETHICAL AI

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