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 [32], 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 [3]. The model, simulating AGI capabilities [6], 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) [25], which closely followed the first breakthrough towards human-like agents: *"Attention Is All You Need"* [33] 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 [19].

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 [30], and even the general public showed great interest once AIs became smart enough: ChatGPT reached one million users in just five days [21], an astonishing feat when compared to other technologies such as personal computers, which needed almost ten years to reach the same milestone [26].

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 [13], and their black-box nature makes it difficult to understand and predict their behavior [36]. Moreover, they are often trained on pirated material, like books [27] or art [20], igniting protests in many creative communities, such as hollywood writers [22] or video game actors [24]. 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 [4, 5]

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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 [15, 31], and can influence public opinion, manipulate elections and pose a threat to public health: the European Union issued guidelines to online platforms and search engines to mitigate the impact on misinformation on elections [1], the World Economic forum has identified the proliferation of false content as the leading short-term global risk in 2025 [7], and a BBC investigation found Russian-funded fake news networks aiming to disrupt european elections [17]. Moreover, fake news on health can cause psychological disorders and panic, fear, depression, and fatigue [28], and the World Health Organization called for the development of international fact-checking organizations to combat this phenomenon [23].

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 [16], citing true evidence to support false claims [11], and inducing the illusion of majority opinion thanks to the sheer volume of information produced [9]. That being said, not all findings are entirely negative: Drolsbach and Pröllochs [10] 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 [12]. 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 [34].

It follows that detecting and mitigating fake news is crucial. From the foundational work by Devlin et al. on *BERT* in 2018 [8], which revolutionized natural language processing trough deep bidirectional transformers, to the application of said transformers in identifying automatically generated headlines, significantly outperforming humans, by Maronikolakis et al. [18], the landscape of automated fake news detection has significantly expanded. Vijjali et al. [35] 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. [14] 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

[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

body. Results can be seen in table 2. Schütz et al. [29] 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. [2] use *Convolutional Neural Networks* (CNN) and *Deep Convolutional Generative Adversarial Networks* (GAN) to detect them with high accuracy, as shown in figure 1.

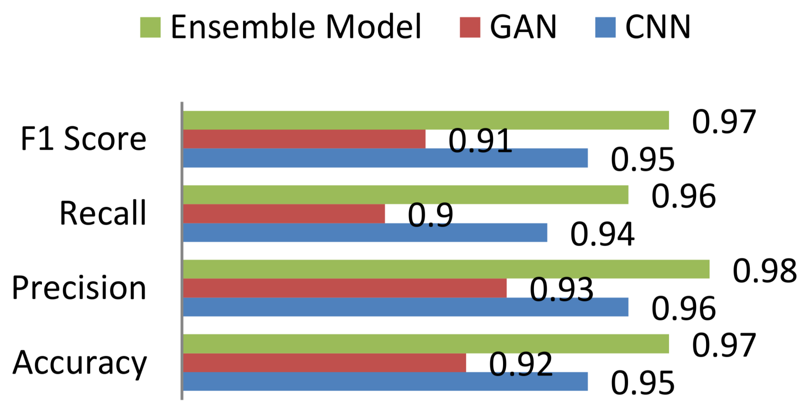

Fig. 1. Transformer models scores on deepfakes detection, Bansal et al. [2]

Table 1. Precision metrics for two-stage transformer model for COVID-19 fake news detection, Vijjali et al [35]

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. [14]

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

3 AI ON HUMANS

4 AI OWN BIASES

5 ETHICAL AI

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