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Humanizing the Forecast: Exploring the Perception of AI-Generated Journalism

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Abstract

Artificial Intelligence is rapidly transforming how information is produced and trusted, with significant social implications. The rise of AI-generated content raises concerns about misinformation, trust, and the loss of human emotion in storytelling, especially in fields like journalism, where clarity, credibility, and emotional resonance shape public understanding and democratic discourse. This study explores AI's impact on weather journalism, a typically data-driven field, focusing on how AI-generated articles can be humanized to improve engagement and trust. We found that while AI content is generally seen as trustworthy and useful, opinions vary on authorship and style. Participants remain skeptical about its emotional depth and accuracy, emphasizing the need for transparency and human oversight.

CCS Concepts

• **Human-centered computing** → **Human computer interaction (HCI)**; • **Applied computing** → **Computers in other domains**; • **Computing methodologies** → **Artificial intelligence**.

Keywords

Generative AI, journalism, forecast

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1 Introduction

Journalism is the practice of researching, composing, and sharing reports about current events and issues through print, broadcast, or digital media. It involves finding and selecting information, crafting

it into coherent stories, and delivering it to the public via newspapers, magazines, radio, television, or online platforms [6]. At its core, journalism aims to keep society informed by providing timely and relevant content that reflects the world around us.

Following this, a foundation of unwavering ethical principles should guide the pursuit and dissemination of information, with truthfulness, objectivity, and accuracy standing as paramount pillars. Truthfulness demands a commitment to factual reporting, context, and transparent sourcing. Objectivity entails striving for impartiality and presenting diverse perspectives fairly. Accuracy necessitates rigorous fact-checking and the correction of errors to maintain credibility [12] [26] [23].

Journalism has been fundamentally reshaped by technological innovations, which have continuously transformed how news is produced, gathered, and distributed. Particularly, the advent of telecommunications enabled remote information gathering via telephone, transcending geographical limitations. Subsequently, radio and television introduced faster formats for news dissemination, reaching wider audiences with greater immediacy. The internet has further revolutionized the field, facilitating reporting and information acquisition and significantly accelerating the overall news cycle. Moreover, the internet provides direct access to a vast repository of public records and corporate information, empowering journalists with non-trivial research capabilities [13].

Building on this ongoing technological evolution, automated journalism has emerged as a significant and rapidly evolving frontier in the field, relying on computer programs and algorithms to generate news content with minimal human input. Automation processes based on machine learning, already applied in many domains [3, 16, 17], are now increasingly used in journalism as well. Automated journalism ranges from simple systems filling templates with data to sophisticated approaches using big data and Artificial Intelligence (AI) to create original stories. Initially prominent in sports [22], these advanced systems analyze vast amounts of data to find patterns and generate engaging narratives [15]. A typical workflow involves first gathering data, like baseball statistics, then algorithms pinpoint significant events, such as exceptional plays or game-changing moments. These insights are ranked by importance, and the software arranges them into a coherent story following pre-set guidelines. Finally, this automatically generated story can be directly sent to a publisher's system for potential immediate release [10]. The software's automated news generation relies on specific,



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pre-defined rules developed collaboratively by engineers, journalists, and computer linguists. For instance, remaining in the sports domain, engineers should embed knowledge of game technicalities in the software, journalists should define what's newsworthy for the algorithm to identify and rank events, and computer linguists should enable sentence construction by analyzing text or, initially, through journalist-written modules [10].

The integration of AI and Machine Learning (ML) into news production offers several key benefits that enhance both efficiency and quality [28]. By automating routine tasks such as data collection, sorting, and basic content generation, AI frees journalists to focus on more complex and insightful storytelling. It enables faster news delivery, especially in high-pressure situations like breaking news, by providing real-time data analysis and content suggestions. AI also enhances investigative journalism through advanced data analysis, uncovering patterns and trends in large datasets. Additionally, personalized news feeds driven by AI improve user engagement by tailoring content to individual preferences. Overall, this integration augments human capabilities and enriches journalistic output with deeper insights and faster, more relevant reporting [28].

While the advantages of employing AI in journalism are becoming increasingly apparent, a balanced perspective necessitates acknowledging the inherent limitations that warrant careful consideration. Several key challenges accompany the integration of AI into news production. Firstly, the potential for embedded biases within the AI's training data cannot be overlooked, raising concerns about the objectivity and fairness of AI-generated content [20]. Secondly, the often opaque nature of AI learning processes can foster distrust among users who may struggle to understand how information is selected and processed [32]. Furthermore, AI currently lacks the nuanced human qualities such as sensitivity, critical analysis, and emotional understanding that are often vital for producing truly in-depth and engaging journalistic narratives [31]. The reliance of AI output on human input also introduces vulnerabilities, as the technology remains susceptible to manipulation by corporate agendas or the biases of the journalists who design the prompts and curate the data sources. Finally, the potential for AI to generate errors and disseminate misinformation [5][27] underscores the critical need for human oversight and rigorous verification processes to ensure the accuracy and reliability of AI-driven journalism.

Building on these considerations, this exploratory study examines the social impact of AI in the specific context of weather journalism, a field traditionally perceived as objective, data-centric, and less prone to the subjective complexities of other journalistic genres. By focusing on this niche yet widely consumed domain, we aim to investigate two central questions: first, how AI-generated weather articles can be humanized through narrative techniques and stylistic enhancements to foster deeper engagement and trust among readers; and second, whether public perception of such AI-driven content shifts when the thematic emphasis of the article moves from purely factual reporting to more interpretative or emotive storytelling. These inquiries not only shed light on the evolving relationship between readers and automated journalism but also contribute to a broader understanding of how AI can be responsibly integrated into media practices without compromising the values of transparency, reliability, accuracy, and human connection. We saw

a generally positive perception of AI-generated articles in terms of trustworthiness, readability, and usefulness, though opinions on authorship and style vary. Factors influencing evaluations included language tone, structural clarity, and the presence of a human voice. While participants were somewhat open to AI-generated content, they remained skeptical about its accuracy and emotional depth, emphasizing the need for transparency and human oversight. The findings highlight the importance of editorial control and public trust in AI writing.

2 Related Work

The automation of journalistic processes has been underway since the late 20th century. Early advancements focused on speech-to-text technologies, exemplified by the Automatic Spoken Document Retrieval system in the late 1980s [25], which facilitated the transcription of broadcast content. This initial foray into automation within newsrooms paved the way for the emergence of full-text generation as a significant tool for numerous media organizations by the mid to late 2000s. This evolution reflects a growing interest in leveraging technology to enhance efficiency and expand the scope of news production.

Building upon these early foundations, several news organizations are actively exploring the integration of AI across various aspects of news production. The Associated Press (AP) serves as a prominent example, utilizing AI-driven tools for tasks such as analyzing video content to generate shortlists, a process that still involves human review and editing. Furthermore, the AP is investigating the potential of AI for article translation and the creation of concise summaries, highlighting the versatility of AI in streamlining workflows and enhancing content accessibility [24]. Beyond workflow optimization, AI is also being deployed for real-time reporting. The Los Angeles Times' Quakebot¹ exemplifies this capability, automatically generating initial news articles based on data from USGS earthquake notifications. This demonstrates the potential of AI to rapidly disseminate critical information in time-sensitive situations. Moreover, initiatives like L.A. Times Voices showcase a move towards more sophisticated AI applications, employing AI-driven analysis ("Insights"²) to contextualize opinion pieces and assess their position within broader societal debates, suggesting a role for AI in enhancing the analytical depth of news coverage.

Given the structured and data-rich nature of domains like weather forecasting, it has been a prime area for the application of automated journalism techniques. The Forecast Generator (FOG) represents a significant advancement in this area, utilizing a sophisticated language model to directly generate weather forecasts from graphical depictions of meteorological data [9]. This approach directly addresses the challenge of translating complex visual information into understandable textual narratives, a core concern within automated journalism.

In [4], researchers presented an early method for generating weather news summaries using fuzzy reasoning and ontologies. Their system utilized weather, time, and geography ontologies to extract key terms from original weather articles, representing these terms through fuzzy sets. Subsequently, fuzzy reasoning was

¹<https://www.latimes.com/la-me-quakebot-faq-20190517-story.html>

²<https://www.latimes.com/insights/>

employed to score sentences, enabling the construction of a summary from the highest-scoring candidates, leveraging data from a weather news website. This work highlights an early attempt to synthesize weather information into concise textual formats using computational intelligence.

This area was further explored in [21] by combining Zadeh's Computational Theory of Perceptions and Semantic Web techniques to develop a framework for generating short, meaningful natural language weather reports. Their framework utilized an ontology to define specific contexts of meaning, ensuring that generated reports were tailored to user needs by focusing on pertinent information and filtering out irrelevant details. This research underscores the importance of context and user-centricity in automated weather reporting.

While the technical capabilities of AI in generating news are evolving, understanding user perception of this content is equally critical. In [33], a cross-cultural experiment was conducted comparing U.S. and Chinese users' evaluations of news reports primed as human-authored or algorithm-generated. Their findings revealed nuanced cultural differences: U.S. participants generally rated human-authored news higher in quality and likability, particularly in traditional media. Conversely, Chinese users showed a preference for algorithm-generated content online. Notably, the study found no significant differences in perceived trustworthiness across both groups, regardless of the media outlet. These findings highlight the complex interplay between cultural context, media format, and user perceptions of automated news, suggesting that algorithmic content's acceptance is not universal and is influenced by various factors. This underscores the need to investigate user perceptions within specific domains like weather forecasting.

A study involving 251 Australian sports fans [7] demonstrated a significant preference for human-written match reports over automatically generated texts, citing higher ratings for enjoyment and liking. While perceptions of arousal and quality did not differ significantly, the consistent perception of distinct differences between human and automated reports across all participants suggests a fundamental difference in how users experience and value different forms of news content. This finding raises questions about whether similar preferences or distinctions exist in the context of weather forecasts, which often serve a more utilitarian purpose than sports reports.

As automated journalism becomes more prevalent, concerns regarding its impact on journalistic practice have emerged. Existing research [2] highlights the potential risk of over-reliance on easily quantifiable data, potentially marginalizing important stories that do not fit readily into discernible patterns.

In [8], ethical debates were investigated among Spanish online media professionals concerning the challenges posed by convergence and multiplatform production. Through a community of practice lens, this work identified emergent standards and practices as a foundation for ethical decision-making in dynamic digital news environments. This research emphasizes the importance of developing shared norms and learning processes to guide the ethical integration of automation in journalism.

In [14], researchers argue that Human-Machine Communication challenges the traditional communication research assumption of

humans as communicators and machines as mediators. This framework prompts a critical examination of the evolving roles of both humans and machines in communication, particularly concerning AI's news-writing function. This perspective underscores the need to theoretically understand the broader implications of AI's influence on the roles of communicators and social relationships and the very understanding of news production.

In [1], an agent-based social platform leveraging artificial intelligence was proposed to enhance media content organization, management, and distribution. While primarily focused on the technical architecture, this work contributes to the broader understanding of how AI can be integrated into media ecosystems. Similarly, recent research exploring intelligent media robots highlights the potential for cost reduction, increased accessibility, and improved journalist productivity, while also acknowledging limitations such as restricted reporting fields and readability concerns [30] [29].

While existing research has explored the technical aspects of automated news generation, including in structured domains like weather, and has begun to examine user perceptions of automated news in general and in areas like sports, there is a notable lack of specific investigation into how users perceive and evaluate AI-generated weather forecast reports. The unique characteristics of weather information, including its potential impact on daily life and the need for accuracy and trust, warrant focused attention. This study aims to address this gap by investigating user perceptions of AI-generated weather forecast reports, contributing to a more nuanced understanding of the human-AI interaction in the context of this specific and crucial information domain.

3 Case study

To investigate users' perception of AI-generated weather forecast articles, we implemented an API (Application Programming Interface) with ASP.NET Core 8 with the purpose of returning an article (including the title) that describes the weather of the requested location for the specified date. This is made possible through an AI engine, which generates the text based on data previously retrieved from the free and open source OpenMeteo API³. In our case study, we focused on the Italian region of Emilia-Romagna and the city of Rimini.

API Call Architecture. The implemented API endpoint is accessed via an HTTP POST request. The request body must specify both the date and the city for which the weather report is desired. An additional feature allows users to omit the city field; in this case, the API generates a general weather summary for the entire Emilia-Romagna region. The API response consists of two elements: (i) the title of the generated article, and (ii) the full body text of the weather article.

Integration with the OpenMeteo API. To generate the required content, the system first retrieves the requested city's geographical coordinates (latitude and longitude). If no city is specified, a loop iterates over all predefined cities within the Emilia-Romagna region (specifically, the province), retrieving weather data for each one and subsequently aggregating the results. For each location, the OpenMeteo API returns the following time-series data:

³<https://api.open-meteo.com>

- (1) a collection of decimal values representing maximum temperature at 2 meters height;
- (2) a collection of decimal values representing maximum wind speed at 10 meters height;
- (3) a collection of decimal values representing minimum wind speed at 10 meters height;
- (4) a collection of numeric weather condition codes (e.g., clear sky, rain, etc.).

Although the OpenMeteo API provides data across multiple hourly intervals, in this implementation, only one representative value per parameter is selected for further processing. Once all required data is collected, average temperature and average wind speed are computed. Wind speed is also translated into a human-readable phrase (e.g., "0" → "no wind") to simplify the AI prompt formulation and avoid overloading the model with low-level data.

Prompt Composition and Interaction with AI model. With weather data prepared, the next step involves composing the prompt for the AI model. The prompt consists of two main sections:

- **Instructional Header:** this section defines the objective of the generation task (i.e., writing a short weather article) and includes two specific configuration parameters for the AI model: (i) Perplexity (PPL) value set to 20, which encourages the generation of coherent and accessible text with a journalistic tone; and (ii) Giant Language Model Test Room (GLTR) value set to 5, indicating a preference for highly natural and human-like outputs.
- **Contextual Data:** this includes the city name, a natural language description of the weather conditions (e.g., "partly cloudy"), the average temperature, and a simplified description of the wind.

Two separate prompts are used:

- (1) "Write a suitable headline for an article presenting weather forecasts."
- (2) "Write a weather article for day {0} in a clear, direct, and comprehensive manner, using a maximum of 300 words. Include the temperature only if you believe it is important. Write for a PPL of 20 and GLTR of 5. Do not use the word "today". Data to be processed: {1}"

The first prompt instructs the model to generate a concise and appropriate title. The second one provides a more detailed instruction aimed at producing a journalistic-style weather article based on the day ({0}) and processed meteorological data ({1}). During early iterations, the model tended to overemphasize numerical temperature values, which often detracted from the clarity and flow of the article. To mitigate this, a specific restriction was introduced in the prompt. Similarly, the usage of the word "today" was explicitly forbidden to ensure that the generated content remains temporally neutral and suitable for integration into dynamically generated web pages. These constraints help ensure the output remains readable, natural, and contextually appropriate without overwhelming the user with unnecessary numerical data.

Since the article and its title are generated in two distinct steps, a chat-based architecture is employed to manage the interaction. This enables message history tracking (both prompts and model responses), which helps avoid token overflow and reduces complexity

in individual prompts. The AI-based text generation is performed using OpenAI, and, for managing the conversational state and interacting with the AI model, the system uses the *ChatCompletionService* provided by Microsoft's *Semantic Kernel*. Once both the article and its title are generated, the API compiles the full response.

3.1 Methodology

This study investigated the perception of AI-generated journalism through a mixed-methods approach involving a two-stage evaluation of news articles and a subsequent survey of attitudes towards AI in journalistic contexts. All the questions asked to the participants are visible in Figure 1.

3.1.1 Article Evaluation Phase (Q1-Q13). Participants engaged in a two-part evaluation of sample weather report articles generated by our API (visible in Appendix A).

- **Initial Blind Evaluation (Q1-Q6):** Participants were first presented with a weather report article and asked to evaluate it based on four criteria using a 5-point Likert scale: trustworthiness, helpfulness, readability, and professionalism. These characteristics align with Lucassen et al.'s framework on information credibility [18, 19], which highlights the role of semantic cues (accuracy, completeness), surface cues (writing style, presentation), and source credibility (expertise, trustworthiness), as well as user-specific needs and processing abilities. Critically, following this evaluation, participants were prompted to indicate whether they believed the article was generated by AI and to provide a brief rationale for their judgment. This step was designed to identify any pre-existing biases or assumptions about AI-generated content.
- **Post-Disclosure Evaluation (Q7-Q13):** Participants were then informed that the article they had just evaluated was, in fact, generated by AI. Subsequently, participants were presented with a second weather report and asked to evaluate it using the same four criteria. They were also asked to indicate whether they believed the article was AI-generated and to explain the reasoning behind their judgment. This allowed for a comparison of perceptions before and after the explicit identification of AI authorship.

3.1.2 Attitude Survey Phase (Q14-Q28). Following the article evaluations, participants completed a series of statements designed to gauge their broader attitudes and beliefs concerning the role and impact of AI in journalism. Stemming from previous studies [11, 19, 31], participants were asked to indicate their level of agreement with 12 statements using a 5-point Likert scale, and answer a closed-ended question and two open-ended questions. This survey explored several key areas, including:

- **Trust and Reliability (Q14-Q16):** Perceptions of the general trustworthiness of AI-generated articles (e.g., "Articles generated by AI are generally trustworthy" - Q14) and comparisons of trust between AI and human-authored content (e.g., "I would consider an article more trustworthy if it were generated by an AI rather than by a reputable newspaper" - Q16).

ID	Questions	ID	Questions	ID	Questions	ID	Questions		
AI-generated articles	Q1-Q7	How trustworthy do you think the article is?	Trust and Reliability	Q14	Articles generated by AI are generally trustworthy	Transparency and Disclosure	Q21	It is important that newspaper articles clearly disclose the use of AI tools in their creation	
	Q2-Q8	How helpful do you think the article is?		Q15	I would consider an article more trustworthy if it were generated by an AI rather than by human		Q22	Knowing the AI model used to generate an article would increase my trust in the content	
	Q3-Q9	How readable do you think the article is?		Q16	I would consider an article more trustworthy if it were generated by an AI rather than by a reputable newspaper		Q23	I think news publishers should be legally required to admit the use of AI tools in writing articles	
	Q4-Q10	How professional do you think the article is?	Bias	Q17	Articles generated by an AI are less biased than articles written by humans		Accuracy and Impact	Q24	AI-generated articles accurately reflect real-world events
	Q5-Q11	In your opinion, was this article written by an AI?		Q18	I am concerned that news generated by AI may contribute to the spread of fake news	Q25		AI-generated articles are less prone to factual errors than human-generated stories	
	Q6-Q12	Please explain the previous answer		Q19	Would your opinion change depending on the content of the article?	Q26		I am concerned that AI is unable to verify the accuracy of information before generating journalistic content	
	Q13	Do you have any suggestions to improve the article and make it seem more "human"?	Q20	Please explain your previous answer	Q27	To what extent do you think AI-generated articles impact the quality of journalism ?		Demographics	Q29
				Q28	Please share your personal feedback on the accuracy of AI-generated articles	Q30	What year were you born in?		
						Q31	What is the highest level of education you have achieved?		
								Q32	What is your main source of information?
								Q33	How often do you use AI tools?
								Q34	What do you use AI tools for?
								Q35	How would you rate your experience using AI tools?

Figure 1: Questions asked in the evaluation phase.

- **Bias and Impartiality (Q17):** Beliefs about the potential for bias in AI-generated articles compared to human-written ones (e.g., "Articles generated by AI are less biased than articles written by humans" - Q17).
- **Misinformation Concerns (Q18-Q20):** Concerns regarding the potential for AI to contribute to the spread of fake news (e.g., "I am concerned that news generated by AI may contribute to the spread of fake news" - Q18). We also examined whether participants' opinions shifted based on the content of the articles (e.g., "Would your opinion change depending on the content of the article?" - Q19). Participants were also given an open-ended question (Q20) to share their personal reflections on the connection between the article's content and their concerns about misinformation.
- **Transparency and Disclosure (Q21-Q23):** Attitudes towards the importance of disclosing AI usage in news articles (e.g., "It is important that newspaper articles clearly disclose the use of AI tools in their creation" - Q21), the value of knowing the specific AI model used (e.g., "Knowing the AI model used to generate an article would increase my trust in the content" - Q22), and support for potential legal requirements for disclosure (e.g., "I think news publishers should be legally required to admit the use of AI tools in writing articles" - Q23).
- **Accuracy and Impact (Q24-Q28):** Beliefs about the accuracy of AI-generated articles in reflecting real-world events (e.g., "AI-generated articles accurately reflect real-world events" - Q24), their susceptibility to factual errors (e.g., "AI-generated articles are less prone to factual errors than human-generated stories" - Q25), their accuracy (e.g., "I am concerned that AI is unable to verify the accuracy of information before generating journalistic content" - Q26), and their overall impact on the quality of journalism (e.g., "To what extent do you think AI-generated articles impact the quality of

journalism?" - Q27). Participants were also provided an open-ended question to share personal feedback on the accuracy of the evaluated articles (Q28).

3.1.3 *Demographic Data (Q29-Q35).* Finally, demographic information (e.g., gender, age, and educational level) was collected from participants, including their primary sources of news and the frequency of their personal use of AI tools. This data will be used to explore potential correlations between participant characteristics and their responses to the core questions regarding the perception of AI-generated journalism.

3.2 Results

A total of 16 participants answered our questionnaire. In terms of gender, the sample included 8 women (53.3%) and 7 men, all aged between 22 and 34 years. In terms of educational background, 9 participants held a Master's degree, 2 a Bachelor's degree, 4 had completed a high school diploma, and one selected "Other". As for their main source of information, 5 participants reported online newspapers, 4 cited television news, and the remaining 7 indicated social networks. Regarding the frequency with which participants use AI tools, the reported average was 3.50 ($\sigma = 1.21$) on a 5-point Likert scale. This suggests a moderate level of engagement, with some variability across respondents. When asked to rate their experience with AI tools on a scale from 1 to 5, participants reported an average score of 3.64 ($\sigma = 0.55$). This indicates a fairly confident level of experience, with relatively low variability among respondents. Participants reported using AI tools for a variety of purposes. The most common uses included search engines (8), writing assistance (8), idea generation (8), coding writing support (8), text translation (3), summarization (5), content generation (including text, images, video, and audio) (6), study support (6), emotional support (1), and work-related support (1). The results of the Attitude Survey Phase are visible in Figure 2 and discussed in the next paragraphs.

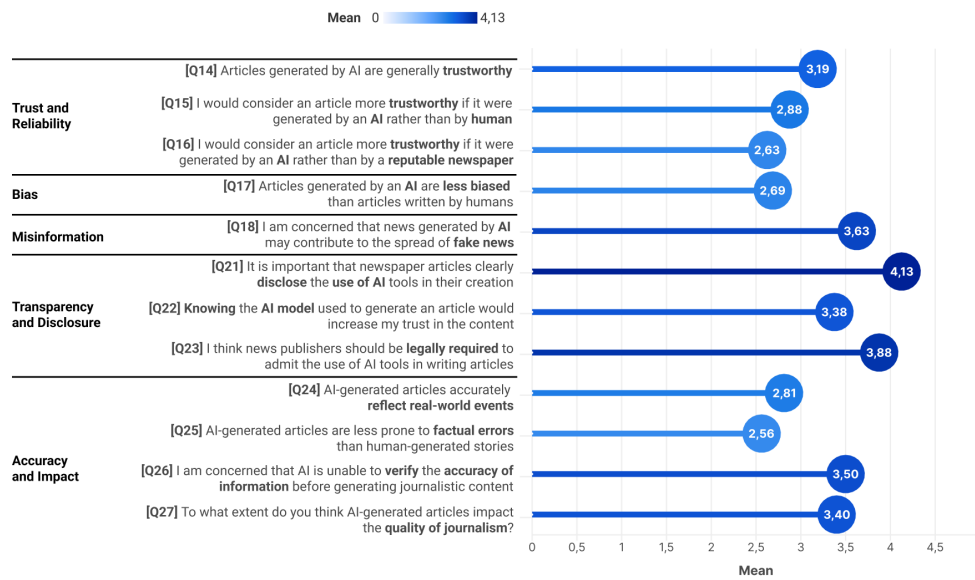


Figure 2: Results of the Attitude Survey questions about trust and reliability (Q14-Q16), bias and impartiality (Q17), misinformation concerns (Q18), transparency and disclosure (Q21-Q23), and accuracy and impact (Q24-Q27).

Article Evaluation. Starting from the blind evaluation of the first article, we observed the following results: the average rating for trustworthiness was 3.38 ($\sigma = 0.96$); usefulness was rated at 3.50 on average ($\sigma = 1.03$); the readability score had a mean of 3.50 ($\sigma = 0.97$); finally, professionalism received an average score of 3.31 ($\sigma = 1.08$). These values indicate a moderately positive perception of the article, with some variation in how participants interpreted each dimension. Regarding the authorship of the article, 10 participants believed it was written by AI, 2 by a human, while the remaining 4 were uncertain. Through thematic analysis of the participants' responses, we identified four main themes influencing their choices: language style, level of detail, content relevance, and structural elements. For 8 participants, the language style played a significant role in shaping their perception and evaluation. Specific aspects mentioned included the use of artificial or unnatural phrasing (e.g., "fresh and sparkling atmosphere"), the tone adopted, verb tense choices, specialized jargon, a linear or overly simplistic style, and sentences perceived as forced or awkward (e.g., P1: "mild or moderate intensity"). 3 participants highlighted the level of detail as a determining factor. References to specific measurements (e.g., P12: "Celsius degrees") and rich, descriptive accounts of phenomena were noted. Two participants pointed to the actual content of the articles as relevant factors: P4 described an article as "useless," while P1 criticized the grouping of cities with similar conditions. Structural aspects were also cited by 2 participants. These responses pointed to the organization and presentation of the information: P7 highlighted the "title divided into two parts and separated by a colon", "short paragraphs", and the "initial and final recap of the overall situation". However, some participants remained uncertain, citing a lack of familiarity with reading such articles or being unsure whether the writing style could be attributed to AI.

Analyzing the results related to the second article, proposed to the participants after the disclosure of the use of AI, we noticed similar values but with a slightly higher level of disagreement between participants: the average rating for trustworthiness was 3.69 ($\sigma = 0.87$); usefulness was rated at 3.38 on average ($\sigma = 1.20$); the readability score had a mean of 3.94 ($\sigma = 0.93$); finally, professionalism received an average score of 3.25 ($\sigma = 1.24$). Despite revealing that the first article was created using AI, participants showed significant differences in their opinions about the authorship of the second article. Specifically, 8 participants attributed it to AI, 4 believed it was written by a human, and 4 were unsure. Common reasons for suspecting AI authorship include a highly organized format (short paragraphs, clear summaries), a descriptive yet impersonal tone (P10: "Using certain ways of describing the weather (feeling fresh, making the air crisper) makes it less direct and too descriptive for a weather article."), and similarities to other AI-like texts (e.g., the first article). Conversely, those who believe it was written by a human point to the expression of human perception (P4: "There are opinions that are less technical and more linked to human perception"), a more conversational tone, and certain word choices (i.e., Anglicisms like "indoor") that feel less mechanical and technical. Uncertain responses highlight the blurred line between human and AI writing, noting that some features could be produced by either, especially if the AI was prompted to write in a more natural style (P5: "It seems less technical-scientific and more readable, but these parameters could have been requested to the AI").

The suggestions for improving the article (Q13) focus primarily on making the language feel more natural and more personal (P1: "perhaps also explaining what activities can be done related to the city"). Some recommend using simpler verb forms, avoiding overly descriptive adjectives, and sticking to more straightforward expressions to enhance clarity and realism (P10: "Use simpler and more

commonly used verb declensions and above all avoid adjectives or long descriptions that can distract from the main information"). A few responses note that the article already seems quite human (P2: "I don't know, also because the difference between a human-written text and an artificial one is already subtle."), while others point out that providing the AI with examples of human-written texts could help it mimic a more authentic tone. Others suggest adding emotional elements or slight imperfections to make the text feel less "perfect" and more human (P3: "a AI-generated article is too perfect, you should add some sentences that also evoke emotions"). There's also a debate about the relevance of a human touch in weather articles, as some believe the topic doesn't necessarily require a personal perspective (P5: "The topic does not require a personal opinion or a "human" point of view." or P12: "Better standardize the language, remaining more scientific and not digressing into real life situations"). Finally, one participant pointed out that when you ask AI to humanize a text, it tends to do so across the entire piece. However, a journalist keeps the professional tone as a foundation and adds a touch of creativity only where needed, in a more targeted way.

Trust and Reliability. Regarding participants' perceptions of trustworthiness in AI-generated articles, responses varied across the three related statements. The statement "Articles generated by AI are generally trustworthy" (Q14) received a mean score of 3.19 ($\sigma = 0.98$), indicating a neutral to slightly positive tendency in perceived trust. However, when comparing AI authorship to human authorship, participants expressed lower levels of trust. The statement "I would consider an article more trustworthy if it were generated by an AI rather than by a human" (Q15) received a mean of 2.88 ($\sigma = 1.02$), while "I would consider an article more trustworthy if it were generated by an AI rather than by a reputable newspaper" (Q16) scored even lower, with a mean of 2.63 ($\sigma = 1.31$). These results suggest that while there is a moderate level of baseline trust in AI-generated content, participants remain more cautious when comparing it directly to traditional human or institutional sources. The increasing standard deviations further indicate greater variability in participants' attitudes, particularly in relation to trusted human-authored sources such as reputable newspapers.

Bias and Impartiality. The statement "Articles generated by an AI are less biased than articles written by humans" (Q17) received a mean score of 2.69 ($\sigma = 1.25$), reflecting a generally skeptical stance among participants. This relatively low average suggests that, contrary to common narratives that portray AI as more neutral or objective, participants may be increasingly aware of the potential biases embedded in AI-generated content. The relatively high standard deviation further indicates substantial variation in individual perceptions, pointing to an ongoing debate or lack of consensus on this issue. Interestingly, this finding highlights a growing public awareness of algorithmic bias and suggests that AI is no longer automatically perceived as impartial. Instead, participants may be recognizing that AI systems can reflect the limitations and biases of the data they are trained on, as well as the choices made by their developers.

Misinformation Concerns. Concerns about misinformation were reflected in the responses to the statement "I am concerned that

news generated by AI may contribute to the spread of fake news" (Q18), which received a relatively high mean score of 3.63 ($\sigma = 1.09$). This indicates a prevalent concern among participants regarding the potential of AI-generated content to disseminate false or misleading information. Further insight into participants' critical engagement with AI-generated news emerged from their responses to Q19. 8 participants (50%) stated their opinions would vary based on the article's content, while 6 participants indicated they would not be influenced by it, and two expressed uncertainty. When it comes to more sensitive or complex subjects, such as medicine or current affairs, people tend to prefer human authorship or, at the very least, expert review (Q13). The main concern is the accuracy and reliability of information, which becomes more critical with the importance of the topic (P13: "Although I believe that the error rate for a human or an AI is the same, in fact if the topic changes my level of trust also changes."). Some believe AI can handle technical or data-driven topics (like weather) more reliably, especially if it's fed accurate and structured data (P7: "In general, I believe that the result always depends on the starting data: the more schematic, reliable and complete they are, the more likely it is that the resulting content will be reliable"). Others stress the need for oversight, regardless of the subject, with AI seen as a useful tool rather than a full content creator (P1: "It depends on whether the article brings news or reports something already consolidated. A rewriting of the form with AI is welcome, but generating content without supervision is not"). A few responses argue that the intent and supervision behind the AI's use matter more than the topic itself (P11: "It always depends on why the article was written and who wanted it. I think it is the person who makes the AI-generated article reliable or not."), while others note that more public education on AI's strengths and limits may be needed (P5: "perhaps an education on the use and enjoyment of AI is necessary").

Transparency and Disclosure. Participants expressed a generally strong preference for transparency regarding the use of AI in journalism. The statement "It is important that newspaper articles clearly disclose the use of AI tools in their creation" (Q21) received the highest agreement, with a mean of 4.13 ($\sigma = 0.81$), indicating a near-unanimous expectation for explicit disclosure. Similarly, the idea that "News publishers should be legally required to admit the use of AI tools in writing articles" (Q23) was also well-supported, with a mean score of 3.88 ($\sigma = 1.37$). This suggests that many participants believe such disclosure should not only be encouraged but also mandated by regulation. In contrast, the statement "Knowing the AI model used to generate an article would increase my trust in the content" (Q22) received a more moderate mean of 3.38 ($\sigma = 1.15$). While this still reflects a general trend toward valuing transparency, it suggests that knowing technical specifics such as the model name or type may be less impactful for building trust than broader disclosure practices. Together, these responses reflect a clear desire among participants for openness in AI-generated journalism, with a particular emphasis on visibility and accountability in the publication process.

Accuracy and Impact. Participants expressed mixed views regarding the accuracy and impact of AI-generated journalism. The statement "AI-generated articles accurately reflect real-world events" (Q24) received a mean score of 2.81 ($\sigma = 1.11$), while "AI-generated

articles are less prone to factual errors than human-generated stories" (Q25) scored even lower, with a mean of 2.57 ($\sigma = 1.46$). These relatively low averages indicate a general skepticism about the factual reliability and comparative accuracy of AI-generated news content. In contrast, the statement "I am concerned that AI is unable to verify the accuracy of information before generating journalistic content" (Q26) garnered the considerably higher mean of 3.50 ($\sigma = 1.21$). This suggests that participants are not only aware of, but also concerned about, the limitations of AI systems in fact-checking and ensuring informational accuracy. When asked "To what extent do you think AI-generated articles impact the quality of journalism?", responses yielded a mean of 3.40 ($\sigma = 0.83$), indicating a moderate perception that AI has a significant effect on journalistic standards. The relatively high score, paired with earlier concerns, could reflect ambivalence or apprehension about the overall influence of AI on the integrity and quality of news media. Together, these responses suggest that while participants acknowledge the growing role of AI in journalism, concerns about factual accuracy and verification remain prominent, potentially influencing how AI-generated content is received and trusted.

The accuracy of AI-generated news depends on several factors, including the topic, how the AI is used, and the expertise of the person guiding it (Q28). While AI can be a valuable tool for improving the structure or clarity of a piece, relying on it to generate content entirely can be risky, especially in fields like medicine or law, where factual errors could have serious consequences (P4). The quality of the output often reflects the quality of the input; a well-crafted and specific prompt can lead to better results (as mentioned by P3 and P10). However, the final responsibility should always lie with a human, who can critically review the information and verify its correctness (P3: "A prompt must be created with accuracy and must always be specific. These tools help humans, who always have the final review, being thinking beings, unlike AI that follows algorithms"). A particularly interesting point of view comes from P13, who stated: "AI is a powerful tool if you know how to use it. My perspective on journalism, however, is currently quite negative, not due to concerns about source reliability, but because of the linguistic style: a journalist is first and foremost a writer, someone with a personal voice and a distinctive style, who often brings their own perspective into the story".

4 Conclusion and Future Work

The study highlights a moderately positive perception of AI-generated articles in terms of trustworthiness, readability, and usefulness, though participants remained divided on authorship and style. Key factors influencing evaluations included linguistic tone, structural clarity, and perceived presence (or absence) of a human voice. While participants showed some openness toward AI-generated content, they expressed skepticism about its accuracy, impartiality, and ability to convey nuanced or emotional depth. Notably, there was strong support for transparency and human oversight. The findings emphasize the importance of editorial control, stylistic authenticity, and public trust.

One limitation of this study is the relatively small sample size, with only 16 participants, which does not fully represent the broader population's views on AI-generated journalism. Additionally, the

study's reliance on subjective self-reports may introduce bias, as participants' personal experiences and prior knowledge could influence their perceptions.

Future research could investigate how different prompt structures influence tone, emotional engagement, and clarity to make AI-generated articles more relatable and credible. Additionally, there is a need to explore how AI-generated content could be tailored to the thematic focus of the article. For instance, extreme weather events may require different prompting strategies compared to routine weather forecasts, as they carry varying levels of emotional weight and urgency. Another avenue for future research is the development of human-AI co-creation models, where AI could serve as an initial content generator, while human editors refine and fact-check the output. Exploring how such hybrid workflows might be perceived in terms of quality, trust, and editorial integrity could be essential in determining how to balance AI automation with the need for human oversight in sensitive areas like journalism. Transparency is another critical area for improvement. Future studies should focus on how to incorporate disclosures about the use of AI in the content creation process. Rather than merely informing readers about the technology behind the article, prompts could be designed to seamlessly integrate these disclosures in a way that enhances trust without interrupting the flow of the narrative. This could include explaining which AI model was used or outlining the sources of information the AI relies on, all while maintaining the integrity and readability of the article.

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A AI-generated articles (translated from Italian)

Article 1: Light Rain and Variable Winds: Weather Forecast for April 17, 2025 in Emilia-Romagna

On April 17, 2025, Emilia-Romagna experiences predominantly unstable weather conditions. Light rain is expected in several cities, with modest intensity concentrated in occasional showers. Bologna, Cesena, Forlì, and Modena will see light rain and average temperatures around 14–15 degrees Celsius, accompanied by a gentle breeze throughout the day.

Ferrara, Ravenna, and Reggio Emilia share similar weather, though distinguished by stronger winds, contributing to a fresher and more brisk atmosphere, with temperatures hovering around 14 degrees.

A different scenario unfolds in Piacenza, where light to moderate thunderstorms bring more dynamic weather and lower temperatures, averaging around 12 degrees. Parma also experiences stronger winds while maintaining the trend of light showers seen across much of the region.

Lastly, Rimini is affected by light but steady rain. The highest temperature of the day, averaging 16 degrees, is paired with more intense winds, creating a consistent cool sensation.

Overall, Emilia-Romagna faces a day marked by variable weather conditions, where the common thread lies in light precipitation and prevalent winds. Caution is advisable for those heading outdoors. Bringing an umbrella could prove to be a wise choice to comfortably manage outdoor activities.

Article 2: Light Rain and Cool Temperatures in Rimini on April 17, 2025

The day in Rimini features rainy weather, with light showers setting the tone for the atmosphere. The sky remains mostly overcast, with brief breaks between the rain. Temperatures hover around 16 degrees Celsius, contributing to a cool sensation enhanced by the humidity in the air.

Although the wind is present, it is not particularly strong, yet it adds a brisk touch to the air. This combination of light wind and rain creates a pleasant setting for those who wish to stroll through the city streets or along the seafront, provided they are equipped with waterproof clothing.

Residents and visitors are advised to carry an umbrella when heading outdoors and to pay attention to potentially slippery road conditions. The day may be ideal for engaging in indoor activities, such as visiting museums or other covered attractions that the city has to offer.

Overall, despite the light rain, Rimini maintains a charming vibrancy typical of spring days. Weather conditions can change rapidly during this season, so it's always helpful to keep an eye on the forecast for any shifts expected later in the afternoon or evening.