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REVIEW

The next media-fueled moral technology panic? News media's and audience's views on ChatGPT

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Abstract
With the diffusion of new technologies, "moral panics" often tend to emerge, with news outlets frequently seen as catalysts. However, empirical evidence on their specific role still remains scarce. The rise of ChatGPT offers a unique chance to observe a new form of moral technology panic in real time. Using a longitudinal survey of a Dutch quota sample and computational content analysis of Dutch news coverage on ChatGPT, we examined whether both news attention and public perceptions of ChatGPT's societal impact increased and became more negative over time. We linked survey-based exposure measures with automated content-analysis-based news characteristics to assess the news media's role in moral panic creation. While the public quickly became aware of ChatGPT, we found no clear indication of a moral panic in the news or among respondents. Moreover, news exposure ultimately did not influence perceptions of ChatGPT's societal impact. We discuss implications for moral panic theories.

Keywords ChatGPT · Moral panics · Longitudinal survey · Automated content analysis · Linkage analysis

1 Introduction

New technologies have always been the topic of morally loaded public discussions (Marwick 2008; Orben 2020; Vanden Abeele and Mohr 2021). Over the decades, these concerns have evolved—from early fears that radio would replace social interaction (Woodford 1929), to worries that computer-mediated communication would erode language skills (Thurlow 2006). More recently, the concern has shifted to social media, with the claim that it is the primary cause of an increase in mental health problems among teenagers (Haidt 2024). These discussions show how technology perceptions and use are socially constructed, meaning that an individuals' evaluation of a new technology as, for instance, helpful or harmful, is shaped through the discourse among members of a society including news media reporting about this technology (Vanden Abeele and Mohr 2021; Wolfers 2024).

Socially constructed negative images of technologies (e.g., as something threatening) have been shown to influence media effects on users (Wolfers et al. 2023) as well as the legislation of the media technology (Marwick 2008). Due to these influences on both the societal level (legislation) and the individual level (media effects), it is important to understand how audience's perceptions and evaluations of technologies are created.

An important theoretical approach to understand the process of social construction of new media technologies is the moral panic approach (Cohen 1973; Critcher 2008). Moral panics are periods of intense and mostly negatively framed discussion surrounding a topic which haves often been observed in response to technological innovations (Marwick 2008). Moral panic theorizing has usually seen news media as important drivers of moral panics (Cohen 1973; Marwick 2008), however, there is limited empirical evidence on the role news media play in the creation of moral panics (Critcher 2008). In particular, few studies

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have examined how audiences and news outlets evaluate a technology in conjunction. The relationship between moral panics occurring in the media and those occurring among audiences therefore remains unclear.

Recently, ChatGPT, an AI chatbot developed by OpenAI that uses machine learning to understand and respond to text inputs, has been identified as a potential focus of the next moral technology panic (e.g., Azrout et al. 2024; Naughton 2023; Rutledge 2023; Van Berlo et al. 2024). Given the early stage of introduction, this provides a unique opportunity to examine the interplay of evaluations of a new technology and its effects on society in the media and among audience members and potentially observe the early stages of a moral panic and the news media's role in panic creation.

In this study, we explore how media exposure to articles on ChatGPT influences changes over time in public awareness, perceived societal impact, and sentiment toward ChatGPT. By linking a multi-wave panel survey — conducted shortly after ChatGPT's initial launch in November 2022 with a content analysis of news reporting on ChatGPT, we aim to examine the role the news media plays in shaping public perceptions and to offer insights into the mechanisms that drive moral technological panics.

2 Moral panics and moral technology panics

Moral panics were first discussed in sociology, where the term was used to describe periods in which a topic or a group of people are subject to intense negative public debate (Critcher 2008). Prominently discussed examples include migration and crime statistics (Critcher 2008; Hall et al. 1978). Moral panics were assumed to share five defining characteristics (Critcher 2008; Goode and Ben-Yehuda 2009): They are marked by an *increasing concern* about a topic, they are characterized by a growing *hostility* toward the designated cause of the concern, and they are marked by a certain level of *consensus* in the public debate about the nature of the threat. Moreover, moral panics are characterized by constructing a threat as *disproportionately* larger than it is and by a relatively short-term *dynamic* in which concerns 'erupt.' Objects of moral panics can be types of crimes and also groups of people, but moral panics have also been described with reference to media technologies (Marwick 2008; Orben 2020; Potter and Potter 2001) such as the social media platform Myspace (Marwick 2008) or cyberpornography (Potter and Potter 2001). In a recent model, Orben (2020) describes the Sisyphean cycle of technology panics in which she describes the reoccurring moral panic cycle reappearing each time a new technology is starting to be adopted by large parts of society.

The model identifies four stages of this cycle: The first stage, *panic creation,* occurs when societal concerns 'accumulate' in public discourse. Drivers of panic creation include technological determinism which refers to the idea that the technological innovation is seen as the main cause and driver of a concerning societal shift and the moralization of the subject in which concerns about dangerous shifts of values are voiced by different actors including news media editors (Orben 2020). In the *political outsourcing* phase, politicians try to respond to the voiced public concerns by funding scientific inquiry into the impacts of the technology on society. Responding to the call, researchers engage in *wheel reinvention* in which they investigate the new technology's impact without building on work on earlier technologies. In the final step, a *new panic* is being created restarting the cycle of technology panics.

The technological innovation of conversational AI, which is based on large language models, such as ChatGPT, is still in an early phase of a potential panic creation. This allows us to study whether the topic is constructed in the public debate as having a large influence on society typical for stances of technological determinism. Moreover, we are able to focus on whether the expected changes are perceived as a threat and therefore whether the influence of these language models on society is mostly described as being negative. Our interest thereby lies in the interaction of news media and their audience.

2.1 The role of news media in moral (technology) panic creation

The important role of news media in panic creation was emphasized in nearly all conceptualizations of the early moral panic literature (Cohen 1973; Hall et al. 1978) but also in the newer examinations of technology panics (Marwick 2008; Orben 2020). The importance of news media can also be seen as a consistent result from previous case studies on moral panics which, however, seldom take a closer look at the connection between news coverage and news users' technology attitudes (for a review see Critcher 2008). Despite the idea having been frequently voiced, the connection between mass media's role and the perceptions of the audience in panic creation is still rarely studied.

We assume that panic creation consists of two substeps in which the audience and news media interact in constructing the new technology as a threat to society. In a first step, the new technology is determined to be important so that attention to the new technology is growing. In a second step, evaluations become increasingly negative constructing the new technology as an increasing driver of negative change in society.

2.2 First step: ascribing importance

The first step of a moral panic is the definition of an issue as a societal threat (Cohen 1973). Breaking down this step into substeps reveals that an important prerequisite of panic creation and social construction of a threat is public awareness of a new technological innovation. Specifically, at the start of the process, the public learns about a new technology and the technology is increasingly portrayed as important by the news media and the public. While ascribing importance has received less attention in moral panic studies, it is one of the main topics of research on innovation diffusion. Diffusion theories, which explain the steps through which a society adopts a new innovation, have thereby identified media as an important source for learning about new technologies (see e.g., Rogers 1983). Toole et al. (2012), for example, showed that mass media attention led to increased adoption of the platform Twitter and studies on other technological innovations, such as autonomous vehicles, confirmed that mass media can be a driver of adoption (Hannan et al. 2023; Zhu et al. 2020).

Thus, we assume that, in the first step of a moral panic, audiences learn — in part through increasing news attention — that a new technology is something important to pay attention to. We suggest three interconnected hypotheses. As moral panics often begin with increased visibility of an issue, we expect that media attention toward ChatGPT increases and that more people learn about ChatGPT over time. As it is unlikely that people easily forget about the existence of a new technology like this, this is a relatively straightforward assumption to make. To go beyond this relatively simple assumption, we will also assess descriptively how quickly the awareness about ChatGPT grows in society. In a third hypothesis, we hypothesize that individuals exposed to more media coverage will become aware of the technology earlier than others.

H1a: News outlets give more attention to ChatGPT over time.

H1b: More people are aware of ChatGPT over time.

H1c: People who were exposed to more media reports on ChatGPT are aware of it earlier.

2.3 Second step: constructing of the technology as a threat

Moral panics are about threats to society (Cohen 1973; Critcher 2008). We connect Orben (2020)'s two panic creation elements of technological determinism and morality to two aspects that we assume should be present in the early stage of a panic creation process: First, we expect that the social construction of a threat involves the assumption that the technology has a large influence on society. Second, the moral aspect of the panic can be captured easiest by looking at the valence of public concerns and discussion: If a technology is constructed as a moral threat its influences should be primarily reported as being negative. Previous literature has shown that new technologies are often associated with concerns. Several content analyses show that technologies are often framed negatively in the media (Størup and Lieberoth 2023; Stern and Burke Odland 2017; Haddon and Stald 2009). While these studies provide relatively consistent evidence that technologies are framed negatively in news media, they do not allow for observations of changes over time. For audience's view on technologies, available data does suggest that views are not that consistently negative. A comparative study shows that, in most countries, more people evaluate social media as being positive for democracy, with the US as an outlier showing a more negative view on social media's effect on democracy. Notably, also in the Netherlands slightly more people (54%) evaluated social media as being bad for democracy (Wike et al. 2022).

There is little research that connects media coverage of technological threats to audience perceptions. In research on where parents and children receive information about risks associated with the internet, news media ranks among the most important sources, suggesting that news media might be an important source for attitude generation of the audience for new technologies (Livingstone et al. 2011; Mascheroni et al. 2014).

Taken together, the available research is limited and lacks data on developments over time making it hard to understand dynamics in media reports and audience's views on technologies as well as their interconnectedness. Our hypotheses concerning dynamics over time are therefore grounded in theoretical assumptions about the early stages of a moral technology panic (Cohen 1973; Critcher 2008; Goode and Ben-Yehuda 2009). These frameworks suggest that in the early phases of an evolving moral panic, both news media coverage and public perceptions tend to increasingly portray the new technology, here ChatGPT, negatively and see it as having a significant influence on society. Moreover, moral panic frameworks suggest that the news media drive audience's perception on ChatGPT.

H2a: News outlets report about a larger influence of ChatGPT on society over time.

H2b: Participants expect a larger influence of ChatGPT on society over time.

H2c: The more individuals are exposed to media content expecting a large ChatGPT influence on society the larger they expect ChatGPT's influence on society themselves.

H3a: The reports on ChatGPT get more negative over time.

H3a: Viewpoints of people on ChatGPT's influence on society get more negative over time.

H3c: The more individuals are exposed to media content which focuses on negative impacts of ChatGPT the more they expect ChatGPT's influence on society to be negative.

3 Method

To answer the hypotheses, a content analysis on the coverage of ChatGPT and a longitudinal survey on the perceptions about ChatGPT were conducted, and these were combined through a linkage analysis. First, we will discuss the content analysis, followed by the survey and finally the linkage analysis. The preregistration of the project can be found on OSF (https://osf.io/sqy9r/).

3.1 Content analysis: sampling

To determine the national coverage of ChatGPT in the Dutch media landscape, offline and online news articles were collected. News article data were collected from the following news outlets: *De Telegraaf*, *Algemeen Dagblad, De Volkskrant*, *NRC Handelsblad*, *Trouw*, *Het Financieele Dagblad*, *Reformatorisch Dagblad*, *Nederlands Dagblad*, *NOS.nl*, *NU.nl* and *Metronieuws.nl*. The news outlets *NOS*, *NU.nl* and *Metronieuws.nl* only operate online. All other news outlets operate both offline (newspaper) and online. These news outlets are among the most read within the Dutch news media landscape (Bakker 2021). In the first week of October 2024, offline and online news outlet data was collected retrospectively for the entire calendar year 2023. Data was collected from three sources: (a) the Nexis Uni database, (b) the AmCAT database, and (c) web scraping.

3.1.1 Nexis uni

Nexis Uni is a database that archives news articles. The database requires a Boolean search string to arrive at the desired news articles. The following search string was used: "Chat-GPT OR Chat GPT OR ChatGPT*." We also filtered for news articles from the calendar year 2023. Except for the websites of *Reformatorisch Dagblad*, *Nederlands Dagblad,* and *NOS*, both offline and online news article data were available from all outlets ($n = 2074$).

3.1.2 AmCAT

AmCAT is a free and open-source initiative from the Vrije Universiteit of Amsterdam that focuses specifically on mining online news data. The same Boolean search string had been used to collect online news items concerning ChatGPT in the year 2023. Except for *Reformatorisch Dagblad*, *Nederlands Dagblad* and *Metrownieuws.nl*, online news item data were available for all news outlets. In total, the AmCAT database yielded 1,086 online news items.

3.1.3 Web scraping

The AmCAT database yielded few news items from *NOS.nl* and *NU.nl* (resp. 36 and 96 news items). To compensate, web scraping was used, involving scripts that automatically saved the content of web pages.[1] Web scraping was conducted in two steps. First, the news websites' own search bar was used to search for 'ChatGPT'. The URLs of the search results were saved. Alternative spellings of 'ChatGPT' ('Chat-GPT' or 'Chat GPT') yielded no additional search results on either website. Second, the web pages of the destinations of the URLs were scraped. In this way, the content of the news articles could be extracted. Web scraping yielded 69 *NOS.nl* and 9 *NU.nl* news articles in 2023. Together with the Nexis Uni and the AmCAT data, this yields a total of 3238 news articles.

After data collection duplicates were removed, reducing the sample size to 2613. To streamline the time frame of survey data collection and news article data, news articles published outside of the months when survey data were collected were excluded: Only news articles published between 1 January 2023 to 31 October 2023 were retained. Within this time frame, there are 2,056 news articles, which make up the final dataset.

3.2 Content analysis: measures

To be able to answer hypotheses H1a, H2a and H3a, three content features were extracted from the news articles: (a) *attention* toward ChatGPT, (b) *sentiment* toward ChatGPT and (c) expected *size of impact* of ChatGPT. Although hypotheses are presented in a different order, sentiment is discussed before size of impact, as one of the impact indicators is derived from the sentiment score.

3.2.1 Attention toward ChatGPT

Attention to ChatGPT is measured as the total number of news articles about ChatGPT per news outlet.

[1] Web scraping was not applied for *Nederlands Dagblad* and *Reformatorisch Dagblad* as the news articles on these websites are mostly behind a paywall, which makes web scraping difficult.

3.2.2 Sentiment toward ChatGPT

The calculation of sentiment of the news articles was done using the following procedure: First, all sorts of references to ChatGPT in the text were streamlined by replacing them with the same term; the term 'ChatGPT' (i.e., instead of 'Chat GPT' or 'Chat-GPT'). Second, in the texts of the news articles, the sentences in which the term 'ChatGPT' is present were identified. Third, the sentences containing the term 'ChatGPT' were automatically translated into English. For this, we used the *OPTUS-MT* translation model (see Tiedemann & Thottingal 2020). Translation was necessary since the sentiment model used is intended for English text. Fourth, we used the sentiment model *yangheng/deberta-v3-base-absa-v1.1* (see Yang et al. 2021, 2023). This model can predict sentiment toward a particular aspect in text, also called aspect-based sentiment analysis (ABSA).

In ABSA, the model' s input includes both text data and a target term for sentiment prediction. This differentiates it from standard sentiment analysis (SA), which relies solely on text data as input. In our case, we predict sentiment toward the term 'ChatGPT.'

The *yangheng/deberta-v3-base-absa-v1.1* was used to predict the sentiment (negative, neutral, or positive) toward the term 'ChatGPT' in each sentence separately. To validate the classifications of the ABSA model, a subset of 100 random sentences was also annotated by a human coder. We found a sufficiently high ordinal Krippendorff's alpha of 0.78 between the model's classifications and the human coder's annotations. Fifth, the classified sentences were used to calculate proportional scores for each news article: The proportion of negative, neutral, and positive sentences toward the term 'ChatGPT' with respect to the total number of sentences in which the term 'ChatGPT' appears.

Finally, sentiment toward ChatGPT is the proportion of positive sentences minus the proportion of negative sentences toward ChatGPT within a news article. Sentiment thus scales from −1 (*all sentences about ChatGPT are negative*) to 1 (*all sentences about ChatGPT are positive*). This is the definite variable by which H3a will be tested.

3.2.3 Size of impact of ChatGPT

Size of impact based on absolute sentiment: Two indicators were analyzed that might signal the stated size of impact of ChatGPT in news articles. The first indicator is taking the absolute sentiment score of a news article. We reasoned that an article expressing a strong sentiment—whether positive or negative—toward ChatGPT, suggests that the news media is taking a stronger evaluative stance about ChatGPT. Reporting with more sentiment about a topic functions as a framing device to enhance a topic's salience (Kiousis 2004), which could signal that the media deems this topic (ChatGPT) to be societally relevant or impactful. The absolute sentiment score ranges from 0 (*all sentences about ChatGPT are neutral or mixed*) to 1 (*all sentences about ChatGPT are either completely negative or positive*).

Size of impact based on potency: As an alternative signal for how the size of the societal impact of ChatGPT is framed, we drew on the concept of potency, defined as "a measure of 'an entity's impact in terms of being big versus little, powerful versus powerless, consequential versus immaterial" (Heise 2002, p. 37). Osgood's semantic differential framework demonstrated that people reflect on a word by its potency (Osgood 1964): People would associate words with having little strength, power or impact (weak words) versus high strength, power, and impact (strong words). We argued that if ChatGPT is discussed using strong wording, it is framed as a powerful and consequential entity, whereas with weak wording it is framed as a powerless and immaterial entity. To assess the potency of wording we made use of the Harvard-IV dictionary. The Harvard-IV dictionary is an English glossary supplemented with semantic labels. A subset of words is labeled according to the potency dimension of Osgoods' semantic differential. The Harvard-IV dictionary contains 755 words labeled as weak and 1,902 words labeled as strong.

In the context of size of impact, the potency labels from the Harvard-IV dictionary were used as follows: First, the automatically translated sentences about ChatGPT into English were taken as a starting point. Second, the number of weak and strong words in the ChatGPT sentences were counted. Third, the number of weak and strong words were divided by the total number of words in the sentences about ChatGPT. These scores thus range from 0 to 1. Size of impact was measured by the proportion of strong words minus the proportion of weak words. Size of impact thus scales from −1 (*all words in the sentences about ChatGPT are weak*) to 1 (*all words in the sentences about ChatGPT are strong*).

3.3 Content analysis: analytical strategy

To test the content-analysis specific hypotheses (H1a, H2a and H3a), several steps preceded. First, from all the content features except the number of ChatGPT news articles, the average content scores for the news articles per news outlet per month were calculated (January 2023 to October 2023).

For the attention score, the sum per news outlet per month was calculated. For each of these variables, this results in 165 data points: There are 17 unique news outlets, each of which has an aggregate score for all 10 months. Since in some cases the data of a news outlet in a month contains no publications, 170 data points are not reached.

Next, these media scores are Z-standardized at the news outlet level; i.e., the Z-standardized scores do not show the absolute values of these scores, but the fluctuation in these scores per news outlet per month. We focused on the fluctuation in publication amount, sentiment, and the size of impact framing (i.e., absolute sentiment and weak versus strong wording), as each outlet could have a differing baseline due to their journalistic style. Given that an outlet's journalistic style tends to be ritualized and therefore relatively stable (Broersma, 2007), we do not expect that the monthly changes in our measures can be explained by changes in journalistic style.

Standard linear regressions and regressions assuming a quadratic influence of month (i.e., y = month + month × the power of 2) were used to infer and test the trends of the aggregated *Z*-standardized content scores per news outlet per month over time.

3.4 Survey: participants and procedure

As for the survey, the sample was drawn from the I&O Research Panel which consists of a database of Dutch individuals aged 18 and up (see preregistrations of the general survey https://osf.io/d958h). Initially, 2216 respondents were recruited in Wave 1 using stratified sampling based on gender, age, education, and region. For a detailed overview of the demographic characteristics of the sample, see Table 7 in the Appendices. Within each consecutive wave, respondents who participated in the previous wave were invited (except that in Wave 4 all respondents participating in Wave 2 were invited). Overall, 1128 respondents participated in Wave 5.

We applied several exclusion criteria to ensure data quality and for modeling reasons. We first applied the quality checks (speeders, straight-liners, and inattentive respondents) as described in the preregistration of the general survey. We applied these checks cumulatively, meaning that only respondents are included that passed the quality checks in all waves they participated in. As a second quality check, we also removed respondents from the data that over time unlearned about the existence of ChatGPT. Although it is in general possible to forget about ChatGPT, it is also possible that respondents learned that they could skip questions by responding to not know about ChatGPT. We therefore opted for the more cautious approach and removed these respondents. We finally removed the oversampled respondents in Wave 4 due to modeling requirements.

Table 1 Sample sizes per wave

Wave	*N*
Wave 2	1212
Wave 3	1083
Wave 4	910
Wave 5	750
At least two (2) obervations	1083
Complete data over five (5) waves	750

A filter was applied in the survey for the questions about perceptions toward ChatGPT, asking these questions only when respondents reported to have heard about ChatGPT. For these variables, we thus will have a smaller sample. The number of valid cases per wave can be found in Table 1.

3.5 Survey: measures

3.5.1 Media use

In parallel with the content analysis, the media use of the following news outlets was surveyed: *De Telegraaf*, *Algemeen Dagblad*, *De Volkskrant*, *NRC Handelsblad*, *Trouw*, *Het Financieele Dagblad*, *Reformatorisch Dagblad*, *Nederlands Dagblad*, *NOS.nl*, *NU.nl* and *Metronieuws.nl*. For offline media use, the following question was used: "How many days in a typical week do you read the following printed newspapers?" And for online media use: "How many days in a typical week do you use the following websites or apps for the news?" Media use thus scales from 0 to 7 for each news outlet.

3.5.2 ChatGPT awareness

To measure awareness of ChatGPT we used the following question: "Have you heard of ChatGPT before?" The answer options were: *No, I have never heard of it*, *Yes, I have heard of it but have not tried it*, *Yes, I have already tried it once or a few times*, or *Yes, I have used it regularly*. The answers were recoded so that all who have never heard of it are coded as 0 and all who have heard of it or who have used it are coded as 1.

3.5.3 ChatGPT size of impact & sentiment of impact

To measure perceptions regarding the size and sentiment of impact toward ChatGPT, bipolar scales were used. For size of impact, the endpoints are: *ChatGPT will have no effect on society at all* versus *ChatGPT will have a large effect on society*. For sentiment of impact: *ChatGPT will make society worse* versus *ChatGPT will make society better*. The scales range from 1 to 7.

3.6 Linkage: matching of survey and content analysis

To be able to answer H1c, H2c and H3c, we linked the content analysis measures to the survey measures. The hypotheses required an individual-level exposure score for specific content; i.e., a rough estimate of the amount and type of ChatGPT news coverage each respondent was exposed to. In line with prior media effects research (e.g., De Vreese et al. 2017; Otto et al. 2024), we multiplied each outlet's number of ChatGPT-related news items and their content-level features (e.g., sentiment) by the respondent's self-reported usage in wave 1 for every outlet and summed the resulting values for each individual.

For H1c, about whether respondents are exposed to more media reports about ChatGPT, we used the formula:

$$AmountChatGPTExposure_{r,t} = ln \sum_{i=1}^{n} OutletUse_{i,r} * OutletAttention_{i,t}$$

Here we multiplied the attention score (i.e., number of articles) for each outlet i at timepoint t with how often respondent r reports using that outlet and summed this for all 17 outlets in our data. Because this leads to a rather skewed variable, we took the natural logarithm. For each time point, we used the media content from the 4 weeks prior to the fieldwork of each wave.

For the other two media exposure hypotheses, we did not merely use the media scores of size of impact of ChatGPT based on absolute sentiment and potency (H2c), and the media scores of the sentiment about ChatGPT (H3c) but also weigh in the attention each outlet pays to ChatGPT. We argue this is relevant as to prevent that outlets with relatively fewer attention weigh in more heavily in the exposure variables. This results in the following formula for sentiment exposure (with equivalent formulas for the size of impact based on absolute sentiment and potency scores):

$$SentimentExposure_{r,t} = \sum_{i=1}^{n} OutletUse_{i,r} * OutletAttention_{i,t} * OutletSentiment_{i,t}$$

Because the media exposure scores are calculated by weighting self-reported use of specific outlets with outlet-level content features from 4 weeks prior to the fieldwork of each wave, we introduce temporal ordering: Content precedes the measurement of public attitudes. Although this does not provide the level of causal identification achieved through experimental designs, the temporal ordering helps address concerns about directionality and moves beyond cross-sectional associations (see e.g., Boukes et al. 2019).

3.7 Linkage: analytical strategy

For H1b, to test whether awareness increases across waves, we focused on the respondents who were not aware of ChatGPT in the previous wave (i.e., were able to learn about ChatGPT since the previous wave) and tested whether proportions indeed differ per wave by Z-tests.

For H1c, logistic regressions were used to predict whether respondents have learned about ChatGPT by the news, with our quantity weighted exposure measure. We stacked the data such that each individual has a unique entry for each wave in the data. We controlled for the wave and accounted for individuals that already learned about ChatGPT in a previous wave by removing the entries of waves when a respondent learned about ChatGPT in a previous wave. We also controlled for demographics (age, gender, education), exposure to television, YouTube, Twitter and TikTok, level of tech optimism and level of digital media literacy.

For H2b, H2c, H3b and H3c, a mixed-effects modeling approach was used to address temporal dependencies and individual-level variation by combining fixed and random effects. The mixed-effects model incorporates an autoregressive (AR1) structure on residuals to account for wave-specific correlations, allowing for variation across waves and individual intercepts and capturing both time-series dynamics and individual-specific trajectories. In addition, for H2c and H3c, we included lagged dependent variables in the multilevel time-series models to measure within-person change to partly rule out baseline and selection effects (i.e., individuals with pre-existing views selecting certain outlets). This allowed us to examine whether changes in perceptions are associated with media exposure over time, net of respondents' prior attitudes.

Including the lagged outcome as a predictor also helps isolate the influence of other independent variables on the outcome, beyond the influence of its past values. This approach robustly estimates the effects of media exposure and individual traits over time. High correlations among independent variables and elevated VIFs (assessed via OLS regressions with clustered standard errors) indicated multicollinearity issues. Thus, all independent variables (excluding dependent variables and controls) were log-transformed to manage skewness, enabling effect sizes to be assessed on a common scale, which facilitated comparison across predictors.

4 Results

4.1 Awareness of ChatGPT

We suggested that news coverage of ChatGPT increases over time (H1a). However, looking at the trajectory in Fig. 1, we see the opposite occurring: Over time, attention toward ChatGPT in the news decreased ($b = -0.05$, $p = 0.048$). Notably, however, this decline was relatively small. Also, attention to ChatGPT in the news fluctuated: It initially increased after which it gradually decreased again over time ($b = 0.35$, $p < 0.001$).

Furthermore, we hypothesized that public awareness of ChatGPT increases over time (H1b). As shown in in Fig. 2, awareness of ChatGPT increased over time. This increase was most pronounced in the initial months following the launch of ChatGPT-3 (before Wave 2) but slowed over time. Table 2 presents the proportions of individuals who became aware of ChatGPT after previously being unaware.

As shown in Table 2, the proportion of people that became aware of ChatGPT is largest in Wave 2, with 56% (95% CI [0.53, 0.59]) of the respondents, and significantly larger than in the other waves (see also Model 1 of Table 3). In the last wave (Wave 5) the proportion is also lowest and significantly lower than in the previous two waves (compared to Wave 3: $p = 0.034$; compared to Wave 4: $p = 0.032$).

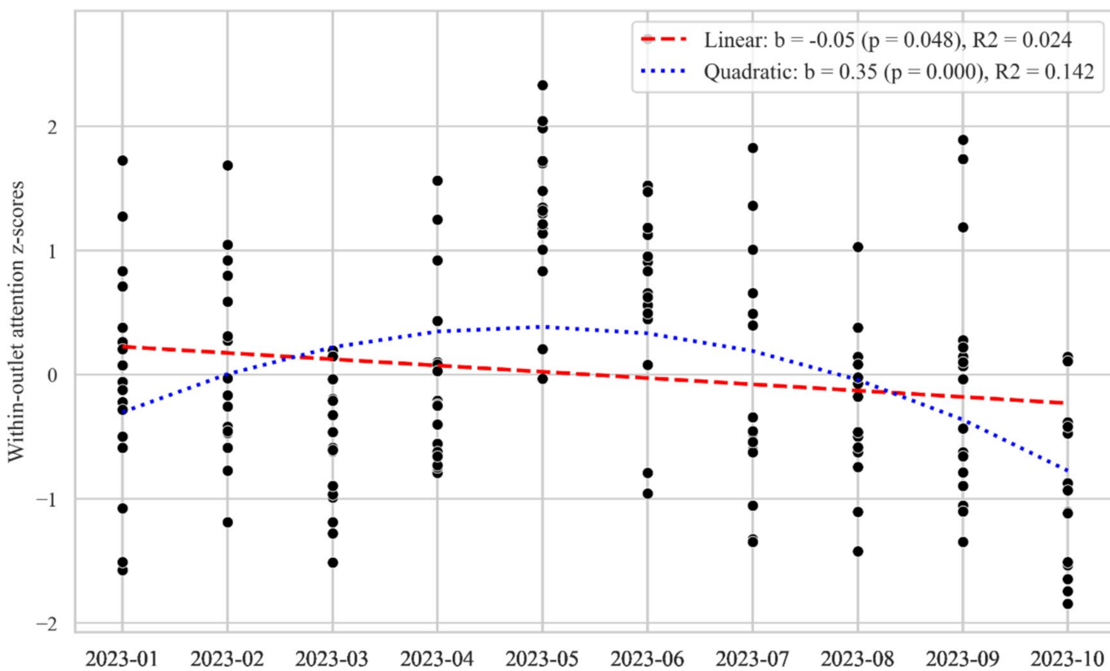

Fig. 1 Within-in news outlet attention to ChatGPT over time

Fig. 2 Awareness of ChatGPT over time. Note. The starting point at 0 was not observed, to build this graph we assume that before the launch of ChatGPT3 in November 2022 only experts working on this topic were aware of it

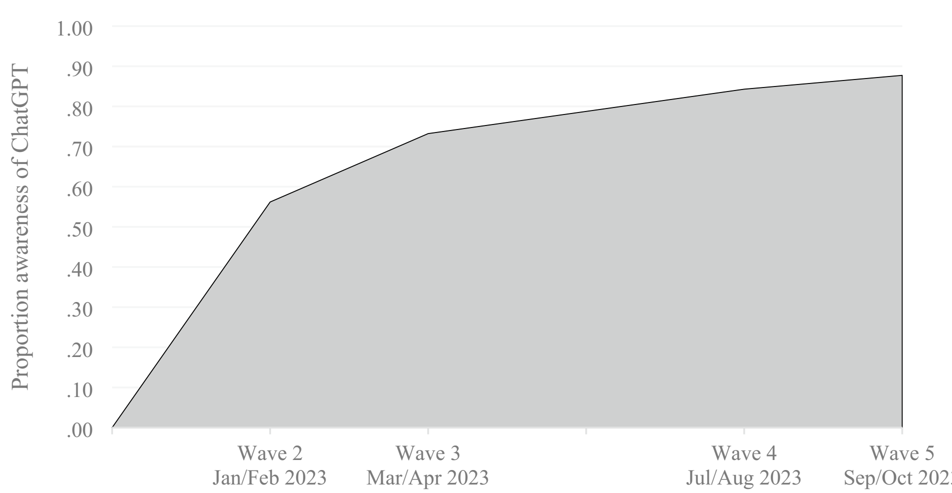

Table 2 Proportions individuals that learned about chatgpt among those previously unaware

Wave	*N*	Proportion	95% CI
Wave 2	1212	0.56	[0.53, 0.59]
Wave 3	466	0.38	[0.33, 0.42]
Wave 4	234	0.39	[0.33, 0.45]
Wave 5	127	0.28	[0.20, 0.36]

Table 3 Logistic regression models predicting learning about ChatGPT

Variable	Model 1	Model 2	Model 3
Constant	0.25^{***} (0.06)	-1.57^{***} (0.41)	-1.76^{***} (0.41)
Wave 3	-0.75^{***} (0.11)	-0.47^{***} (0.12)	-0.42^{***} (0.12)
Wave 4	-0.70^{***} (0.15)	−0.24 (0.16)	−0.22 (0.16)
Wave 5	-1.22^{***} (0.21)	-0.62^{**} (0.22)	-0.62^{**} (0.22)
Quantity of exposure			0.1^{***} (0.03)
χ^2	82.34^{***}	338.06^{***}	352.15^{***}
-2 log likelihood	2741.70	2485.98	2471.89
Nagelkerke R^2	0.05	0.20	0.21
Cox & Snell R^2	0.04	0.15	0.16

Entries are logistic regression coefficients with standard errors in parentheses. In Models 2 and 3 we control for age, gender, education, television news exposure, YouTube, Twitter use, TikTok use, technology optimism and digital media literacy, but to keep the table more concise they are not shown in the table. Please see Appendix Table 8 for the full models. $N_{observations} = 2039$; $N_{respondents} = 1212$

$^{***}p < .001$. $^{**}p < .01$. $^{*}p < .05$

Between Waves 3 and 4 there does not seem to be a significant difference, but we should also note that before Wave 4 the timespan is about twice as large as the timespan before Wave 3, so a similar proportion learning about ChatGPT before Wave 4 did also occur over a longer time.

Next, we expected that individuals exposed to more media reports on ChatGPT would become aware of it earlier (H1c). We tested this using three logistic regression models predicting awareness. The first model only includes the waves and was already used to test the differences in learning about ChatGPT between the waves (as discussed around H1b). The second model includes all the control variables, and in the third model we add quantity of exposure which tests our hypothesis.

When comparing Model 3 to Model 2, we observe that the addition of quantity of exposure significantly improves the model ($\chi^2_{df=1} = 14.09$, $p < 0.001$). The coefficient of quantity of exposure is significant and positive ($b = 0.10$, $SE = 0.03$, $p < 0.001$), which implies that more exposure leads to more learning. To get a sense of what the positive coefficient implies (as the interpretation of logistic regression coefficients are notoriously difficult), we estimated what proportions learning about ChatGPT the model predicts depending on specific values of quantity of exposure while keeping all the other predictors at their mean. When also quantity of exposure is at its mean, Model 3 predicts that 49% of the respondents would learn about ChatGPT. For values of one standard deviation below and above the mean of quantity of exposure, the model predicts 45% and 54%, respectively would learn about ChatGPT. This nearly 10-%-point gap between ± 1 standard deviation is substantial and supports our hypothesis (H1c).

4.2 Size of impact of ChatGPT

Regarding the size of impact of ChatGPT, we hypothesized that news outlets would increasingly report on ChatGPT's growing influence on society over time (H2a). However, no significant linear increase or decrease over time was observed for either the absolute sentiment-based or the potency-based proxy for size of impact (respectively, $b = -0.01$, $p = 0.578$ and $b = 0.02$, $p = 0.337$). Based on these measures, the assumed size of ChatGPT's influence on society in the news appears to be unaffected by time. H2a is rejected.

As an exploratory analysis, we examined the underlying indicators of the potency-based measure for size of impact: The proportion of weak and strong words used in the news articles concerning ChatGPT. Although there is no consistent pattern with regard to the proportion of strong words, there is one with regard to the proportion of weak words: Over time, the use of weak words in news articles on ChatGPT is steadily decreasing ($b = -0.07$, $p = 0.004$), see Fig. 3. Here, it mirrors the quadratic trend of the news attention to ChatGPT: The use of weak words steadily decreased, and then slowly rose again ($b = -0.41$, $p < 0.001$).

Furthermore, we hypothesized that ChatGPT's societal influence will grow over time (H2b). Contrary to our expectations, the results consistently show negative coefficients for the time variable (i.e., Wave) across all models (ranging from −0.09 to −0.11, $p < 0.01$; see Table 4 and Table 5). These results suggest a decline in ChatGPT's perceived societal influence over time.

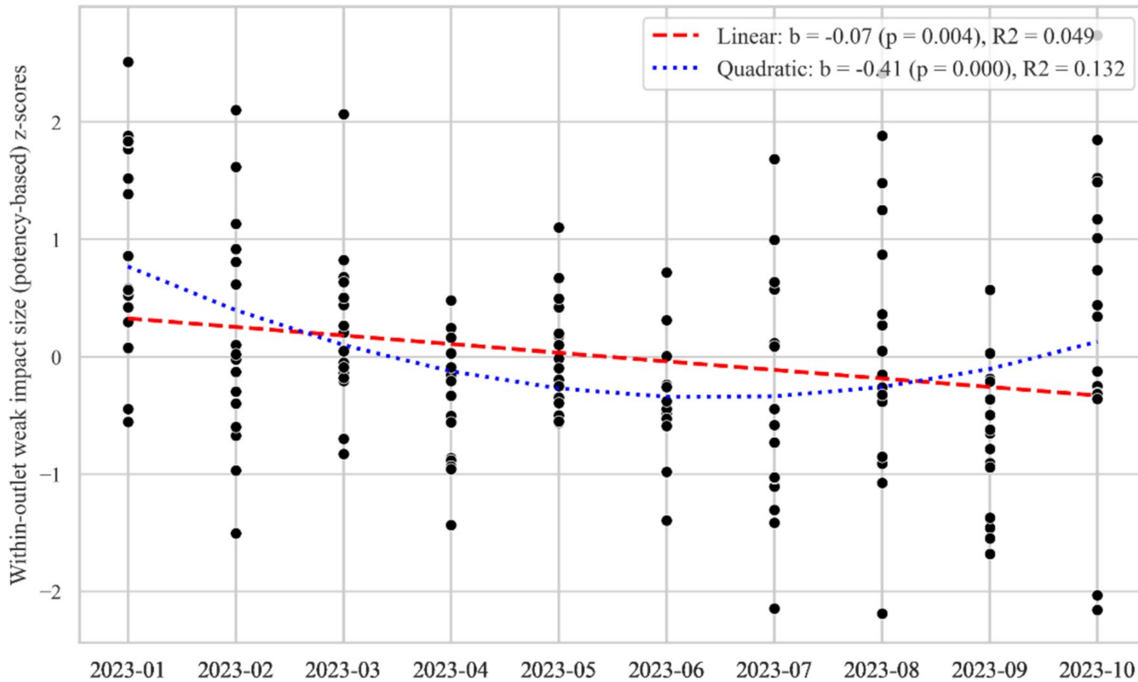

Fig. 3 Within-in news outlet use of weak words about ChatGPT over time

Table 4 Mixed regression models predicting perceived impact ChatGPT

Variable	Model 1	Model 2	Model 3
Fixed effects			
Constant	0.35*** (0.07)	0.15 (0.11)	0.15 (0.11)
Lag impact size	0.51*** (0.03)	0.52*** (0.02)	0.52*** (0.02)
Wave	−0.09*** (0.02)	−0.10*** (0.02)	−0.10*** (0.02)
Absolute sentiment			-0.00 (0.02)
Random effects			
ID (Intercept)	0.10 (0.07)	0.08 (0.06)	0.08 (0.06)
Residual variance	0.59 (0.08)	0.06 (0.08)	0.06 (0.08)
AR(1)	−0.29 (0.06)	−0.31 (0.06)	−0.31 (0.06)
Model fit statistics			
Log seudolikelihood	−2352.90	−2332.89	2332.89
Wald $\chi^2(2)$	455.55***	624.12***	629.46***

Al variables in the models are standardized. Entries of the fixed effect models are regression coefficients with standard errors in parentheses. In Models 2 and 3 we control for age, gender, education, television news exposure, YouTube, Twitter use, TikTok use, technology optimism and digital media literacy, but to keep the table more concise they are not shown in the table. Please see Appendix Table 9 for the full models. $N_{observations} = 1916$; $N_{groups} = 843$

$^{***}p < .001$. $^{**}p < .01$. $^{*}p < .05$

Also, we hypothesized that greater exposure to media portraying ChatGPT as highly influential leads to increased expectations of its societal impact (H2c). This hypothesis is tested using two series of mixed regression analyses containing multiple models. Our results did not support our assumption. No significant effects were found for the different operationalizations of the size of impact media scores — the media score based on absolute sentiment news exposure (Table 4, Model 3), and the media score(s) based on strong versus weak impact wording news exposure (Table 5, Model 3).

4.3 Sentiment of impact of ChatGPT

Regarding the sentiment of impact of ChatGPT, we first of all expected the reports on ChatGPT to become increasingly negative over time (H3a). However, we see no significant upward or downward trend in sentiment: Within news outlets, sentiment toward ChatGPT in news items is relatively stable ($b > -0.01$, $p = 0.885$).

As an exploratory analysis, we examined the underlying scores of sentiment: The proportion of negative, neutral and positive sentences about ChatGPT. Here we see that the proportion of negative sentences about ChatGPT actually decreased ($b = -0.07$, $p = 0.005$), and the proportion of neutral sentences about ChatGPT increased ($b = 0.07$, $p = 0.007$), see Fig. 4 and 5 respectively. There is no significant trend in the number of positive sentences about ChatGPT. H3a is rejected.

Table 5 Mixed regression models predicting perceived impact ChatGPT

Variable	Model 1	Model 2	Model 3
Fixed effects			
Constant	0.35*** (0.07)	0.15 (0.11)	0.10 (0.12)
Lag impact size	0.51*** (0.02)	0.52*** (0.02)	0.51*** (0.02)
Wave	−0.09*** (0.02)	−0.10*** (0.02)	−0.08*** (0.03)
Strong impact news			−0.06 (0.06)
Weak impact news			0.09 (0.06)
Random effects			
ID (constant)	0.10 (0.07)	0.08 (0.06)	0.09 (0.06)
Residual variance	0.59 (0.08)	0.06 (0.08)	0.59 (0.08)
AR(1)	−0.29 (0.06)	−0.31 (0.06)	−0.30 (0.06)
Model fit statistics			
Log Pseudolikelihood	−2352.90	−2332.89	−2331.84
Wald $\chi^2(2)$	455.55***	624.12***	616.34***

Al variables in the models are standardized. Entries of the fixed effect models are regression coefficients with standard errors in parentheses. In Models 2 and 3 we control for age, gender, education, television news exposure, YouTube, Twitter use, TikTok use, technology optimism and digital media literacy, but to keep the table more concise they are not shown in the table. Please see Appendix Table 10 for the full models. $N_{observations} = 1916$; $N_{groups} = 843$

$^{***}p < .001$. $^{**}p < .01$. $^{*}p < .05$

Second, we hypothesized that perspectives on ChatGPT's societal impact become more negative over time (H3b). This hypothesis we tested using a single model. The time variable (Wave) shows a positive coefficient of 0.07 ($p < 0.01$; see Table 6, model 1), suggesting a slight trend toward more positive perceptions of ChatGPT's influence over time. This finding contradicts H3b, implying that views on ChatGPT's societal influence are not becoming increasingly negative but may rather be leaning toward a more positive outlook.

Finally, we expected that greater exposure to media content emphasizing ChatGPT's negative aspects would lead to more negative societal expectations (H3c). We tested this hypothesis using a mixed regression analysis. The model contains predictor variables for negative, neutral, and positive news coverage (see Table 6, Model 3). Although effects run in the expected direction, none of these variables has significant coefficients, suggesting no direct effect of exposure to specific news sentiments on expectations. These results imply that exposure to different tonalities in media content does not directly influence valence attribution among the public.

5 Discussion

This linkage study examined how media exposure influenced changes over time in public awareness, perceived societal impact, and sentiment toward ChatGPT. Our goal was to determine whether the early stages of a moral technology panic about conversational AI could be observed and to test the assumption of moral technology panic theories that news media shape audience perceptions of technologies as threats.

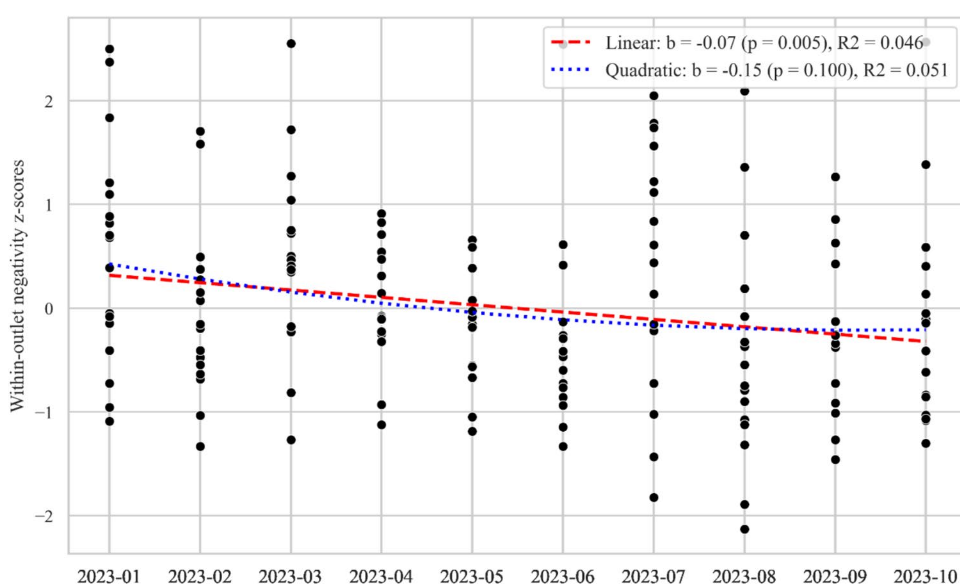

Fig. 4 Within-in news outlet proportion of negative sentences about ChatGPT over time

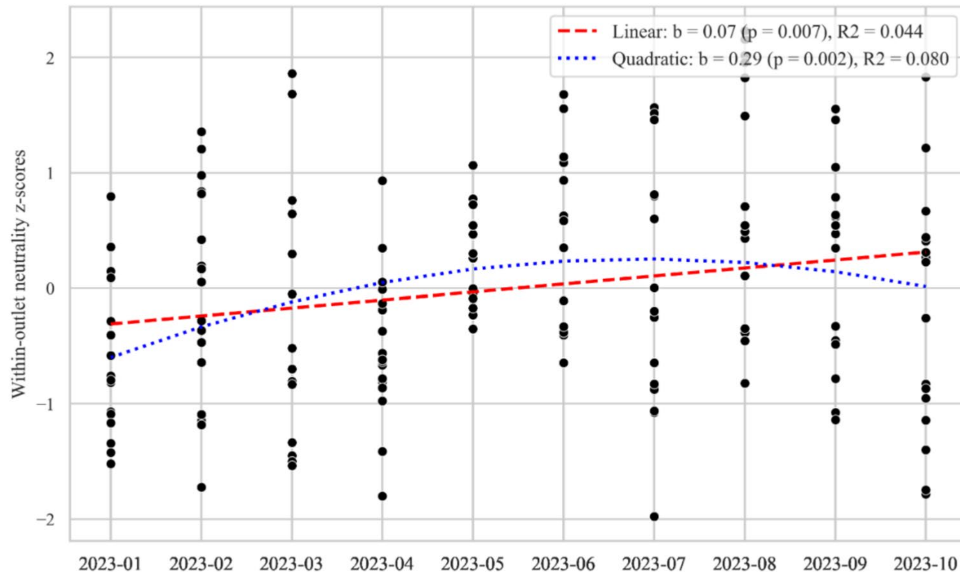

Fig. 5 Within-in news outlet proportion of neutral sentences about ChatGPT z-scores over time

Table 6 Mixed regression models predicting valence regarding impact ChatGPT

Variable	Model 1	Model 2	Model 3
Fixed effects			
Constant	−0.17* (0.07)	0.03 (0.09)	0.03 (0.10)
Lag impact size	0.75*** (0.02)	0.65*** (0.02)	0.65*** (0.02)
Wave	0.07*** (0.02)	0.08*** (0.02)	0.09*** (0.02)
Negative news			−0.01 (0.04)
Neutral news			−0.01 (0.03)
Positive news			0.04 (0.03)
Random effects			
ID (Constant)	< 0.01 (< 0.01)	0.01 (0.03)	0.01 (0.03)
Residual variance	0.68 (3.44)	0.62 0.05)	0.62 0.05)
AR(1)	−0.38 (4.69)	−0.36 (0.05)	−0.36 (0.05)
Model fit statistics			
Log Pseudolikelihood	2272.97	−2222.33	−2220.16
Wald $\chi^2(2)$	1529.69***	1872.24***	1929.99***

Al variables in the models are standardized. Entries of the fixed effect models are regression coefficients with standard errors in parentheses. In Models 2 and 3 we control for age, gender, education, television news exposure, YouTube, Twitter use, TikTok use, technology optimism and digital media literacy, but to keep the table more concise they are not shown in the table. Please see Appendix Table 11 for the full models. $N_{observations} = 1916$; $N_{groups} = 843$

$^{***}p < .001$. $^{**}p < .01$. $^{*}p < .05$

Our results can be summarized in three overall conclusions. First, our results indicate that the awareness about ChatGPT increased quickly showing that we studied a crucial period during which a large portion of Dutch society became aware of ChatGPT. Second, our findings do not indicate that a moral panic about ChatGPT emerged in Dutch public opinion during our study period. Third, our linkage analyses provided insights into how information about technologies presented by news media influences audience perceptions of technology. We will discuss these three points in more detail in the following.

5.1 A sharp increase in ChatGPT awareness

ChatGPT was introduced in November 2022. Our study period in which we asked a representative sample of Dutch adults about their knowledge of ChatGPT captures the time between January 2023 until October 2023. During this ten-month period, nearly 90% of Dutch participants became aware of ChatGPT. We must consider that asking about ChatGPT may have influenced participants' awareness itself. We also need to consider that online access panels such as the one by I&O used in this study might include more individuals who are generally open toward technologies. Still, the increase in such a short amount of time is noteworthy and shows the speed with which we can expect that conversational AI like ChatGPT will be adopted by many groups of society. Adoption cycles of new technologies have become increasingly fast (Comin and Hobijn 2010; Rosa 2013). The adoption of chatbots such as ChatGPT can be seen as a continuation of acceleration of technology adoption observed in the last decades which can be connected to an acceleration of many other societal processes (Rosa 2013). Using a social acceleration lens (Rosa 2013) to explore not only the speed of adoption of ChatGPT into society but also the acceleration of tasks which might become possible with AI-based Chatbots could be particularly insightful in the upcoming years.

5.2 No ChatGPT moral panic?

Our second conclusion, based on both survey responses and media content, is that there are no indications of a moral panic occurring in Dutch public opinion or news media. Perceptions of ChatGPT's expected impact and sentiment were neither particularly strong nor negative. If any trends emerged, they were contrary to our expectations. Taking the Sisyphean cycle of technology panics as a theoretical basis (Orben 2020), which assumes that with the introduction of a new technological innovation a panic is very often created, this is surprising. There are three possible explanations for this finding.

A first explanation would be that ChatGPT may differ from previous technologies. One could argue that ChatGPT and similar chatbots and AI-based tools have the potential to influence more or different areas of society than previous technological innovations such as social media. Dahline (2024) for instance, argued that AI-based chatbots are expected to differ from previous technological innovations by mostly affecting the jobs and lives of highly-skilled workers (e.g., Dahlin 2024). Moral panic theorizing suggests that discussions around negative impacts of new technologies mostly concerned vulnerable populations (Critcher 2008). A moral panic around ChatGPT might therefore be less likely as a moralized debate at the stage of ChatGPT use in 2023. This explanation implies that moral technology panic theorizing needs to take the technology's characteristics or usage groups into account to further refine its predictions. A second explanation could be that societies have evolved and learned how to better deal with technological innovation by a less dramatic way of news media reporting and by intervening earlier with regulations without a prior necessity of moral panic. Indeed, attempts to regulate large language models are already discussed and partly implemented in the political sphere (Veale and Borgesius 2021), possibly based on an increasing competence of political institutions in the field of technology and innovation. It is important to monitor how quickly such regulations are implemented and how effective they are to assess this potential explanation.

Also, for news media it might be the case that with the increasing speed of introductions of technological innovations, journalists learned how to report about them in a less dramatic manner. Kleinnijenhuis et al. (2015), for instance, showed that for the financial crisis the complexity with which news media reported increased over time. The increase in neutral sentences might indicate that such additional complexity in reporting can be also observed for ChatGPT. Such developments in the political and media spheres could suggest that the Sisyphean cycle of technology panics (Orben 2020) and other moral panic theorizing (e.g., Cohen) may no longer accurately represent public discourse on technological innovations. Theories of middle range (Merton, 1968) which are often used in the social sciences are theories which are assumed to hold for a certain geographic area in a certain time period. Our results could indicate that moral panic theories might have reached a temporal boundary so are not applicable to current technology debates anymore. However, before this quite fundamental conclusion can be drawn, we need to consider that it is also possible that a moral panic has not happened yet.

A third explanation is accordingly that a moral panic was not happening yet. Previous moral panics were often tied to young audiences; most frequently children and adolescents (e.g., Critcher 2008). While adolescents are likely already using ChatGPT, children might still not use it extensively yet. Thus, it is possible that a moral panic around conversational AI such as ChatGPT might still be formed once effects on children are more apparent or once the usage has reached a more fundamental level than what could be observed in 2023.

5.3 A missing link between media reporting and audience evaluation

Our third set of conclusions concerns the linkage between the news media reporting and audience attitudes. Our results show that people seem to learn about ChatGPT, at least in part, from traditional news outlets. However, we did not find the expected relationship between the participants' evaluation of ChatGPT's influence on society and the associated media reporting of their preferred media outlets. This could have a theoretical or a methodological reason. On a theoretical level, it could be that the main assumption of moral panic literature that media fuel moral panics does not hold as audiences do not take over news media's evaluation. It needs to be noted that, as we do not find an indication of a moral panic, we cannot test this assumption in the context of an actual moral panic. Thus, future research studying the connection of mass media evaluations to their audience's technology perceptions during a moral panic would be necessary for an accurate test of the theoretical prediction of mass media as drivers of moral technology panics.

A methodological reason could lie in the way our linkage analyses was conducted calculating exposure scores based on participants' usual news media consumption. This traditional way of a linkage analysis seems to be able to explain learning of audiences for the awareness measures and thus seems to be still relevant. However, this paper's measure of attention scores can only approximate actual engagement with articles on a given topic. Thus, a combination with tracking data measuring the articles participants have actually read, could provide a more complete picture of how news use impacts audience learning about a technological innovation (Otto et al. 2024).

5.4 Limitations and suggestions for future research

Our goal with the linkage analyses was to examine the role of media in the creation of a moral panic. However, given the apparent absence of a moral panic surrounding ChatGPT in both news media and the public, our dataset may not be suited to testing the media's role in moral panic formation. Future observations on whether a moral panic emerges could make it valuable to revisit our analysis and results to assess whether the observed trends and relationships still provide insights into the early stages of moral panic formation around new technologies.

That said, our results must be interpreted in light of the limitations of our data collection and analysis. First, as our sample was not drawn by a probabilistic sample, it could be that our survey results are biased and cannot be generalized to the Dutch population. Second, the news media use on which the linkage analysis was built was based on Wave 1 data on respondents' typical news use. Thus, this can only be an estimate of participants' actual articles about ChatGPT they saw.

Third, as is common in computational content analysis, our indicators for sentiment and impact size may only partially capture the more nuanced framing found in news articles. In particular, we found no existing (automated) content-analysis indicators in the literature to capture how the size of ChatGPT's societal impact is framed. Therefore, our use of absolute sentiment and Osgood's potency scale as proxies represents a novel approach. While these measures offer initial insights, a more advanced computational or manual content analysis could yield a more comprehensive understanding of how ChatGPT was portrayed in news coverage during the early stages of its introduction. Future research could build on this by developing and validating more refined content measures to assess how the size of ChatGPT's societal impact is framed.

5.5 Conclusion

To summarize, our study provides longitudinal analyses of attitudes and attention toward ChatGPT by the public and by news media. We show that within the first year of ChatGPT's introduction to regular users, most members of Dutch society became aware of its existence. Moreover, our findings indicate that, contrary to expectations about societal reactions to new technological innovations, there is no evidence of a moral panic. Finally, our data suggest that while news users learn about technological innovations through the media, the adoption of evaluations regarding technologies like ChatGPT may be more complex than previously assumed. Our study serves as a valuable starting point for further observing public debate on conversational AI and their societal influence.

Appendix

See Tables 7, 8, 9, 10, 11.

Table 7 Question wording and descriptives of variables in the survey

Variable	Question wording	Range		Wave 2	Wave 3	Wave 4	Wave 5
			N	1212	1083	910	750
Age	What is your date of birth? *Provided by panel company as a recode into age*	18–88	Mean SD Range	53.11 16.12 18–88	53.54 16.09 18–88	53.90 15.99 18–88	54.40 16.03 18–88
Gender = female	What is your gender? 1. *Male* 2. *Female* 3. *Other* *Recoded into a dummy variable with female as 1*	0–1	Mean SD Range	0.46 0.50 0–1	0.46 0.50 0–1	0.45 0.50 0–1	0.45 0.50 0–1
Education = low	What is the highest education you followed? *This education does not have to be completed* *Are you a student? Then enter the education you are currently following* *Dutch 7 level education scale, recoded into three categories, and here recoded into a dummy variable with lower education as 1*	0–1	Mean SD Range	0.20 0.40 0–1	0.21 0.41 0–1	0.22 0.41 0–1	0.23 0.42 0–1
Education = medium	What is the highest education you followed? *This education does not have to be completed* *Are you a student? Then enter the education you are currently following* *Dutch 7 level education scale, recoded into three categories, and here recoded into a dummy variable with medium education as 1*	0–1	Mean SD Range	0.39 0.49 0–1	0.38 0.49 0–1	0.38 0.49 0–1	0.38 0.49 0–1
Education = high	What is the highest education you followed? *This education does not have to be completed* *Are you a student? Then enter the education you are currently following* *Dutch 7 level education scale, recoded into three categories, and here recoded into a dummy variable with higher education as 1*	0–1	Mean SD Range	0.41 0.49 0–1	0.41 0.49 0–1	0.40 0.49 0–1	0.39 0.49 0–1
Television news exposure	How many days in a typical week do you watch the following television programs? a. NOS Journaal b. RTL Nieuws c. Hart van Nederland d. EenVandaag e. EditieNL 0. *0 days* 1. *1 day* 2. *2 days* 3. *3 days* 4. *4 days* 5. *5 days* 6. *6 days* 7. *7 days*	0–35	Mean SD Range	7.53 7.00 0–35	7.60 6.98 0–35	7.59 7.03 0–35	7.53 6.90 0–35
YouTube use	How often do you use the following platforms / apps? - YouTube 1. *Never* 2. *Less than once a week* 3. *About once a week* 4. *Several times a week* 5. *About once a day* 6. *Several times a day* 7. *Almost all the time*	0–6	Mean SD Range	2.34 1.61 0–6	2.34 1.62 0–6	2.34 1.62 0–6	2.29 1.62 0–6

Table 7 (continued)

Variable	Question wording	Range		Wave 2	Wave 3	Wave 4	Wave 5
Twitter use	How often do you use the following platforms / apps? - Twitter 1. *Never* 2. *Less than once a week* 3. *About once a week* 4. *Several times a week* 5. *About once a day* 6. *Several times a day* 7. *Almost all the time*	0–6	Mean SD Range	0.69 1.52 0–6	0.67 1.51 0–6	0.69 1.53 0–6	0.66 1.49 0–6
Tiktok use	How often do you use the following platforms / apps? - TikTok 1. *Never* 2. *Less than once a week* 3. *About once a week* 4. *Several times a week* 5. *About once a day* 6. *Several times a day* 7. *Almost all the time*	0–6	Mean SD Range	0.26 0.96 0–6	0.22 0.89 0–6	0.22 0.91 0–6	0.21 0.88 0–6
Technology optimism	Please indicate below to what extent you agree or disagree with the following statements a. New technologies contribute to a better quality of life b. Technology gives people more control over their daily lives c. Technology makes me more productive in my personal life *0. Strongly disagree* | *6. Strongly agree*	0–6	Mean SD Range Cronbach's α * This variable was measured in wave 3. To give the respondents in wave 2 that dropped before wave 3 a score in this variable, regression imputation was used	3.10* 1.16* 0–6	3.10 1.22 0–6 .81	3.12 1.22 0–6	3.14 1.21 0–6
Digital media literacy	Do you recognize yourself in the following statements? Think about the extent to which each sentence applies to you, if you would have to do this activity now and without help. Please be honest. It is very normal that you never do some things. We'd like to know this! If you don't understand what the question means, please choose 'I don't understand the question.' a. I know how to choose good keywords for online searched (for example with Google) b. I know how I can find answers to my questions on the internet c. I know how I can use search functions in search engines (for example with Google) d. I know how I can check if the information I find on the internet is true e. I know how I can check if a website is reliable f. I can assess what the goal of online information is (e.g., to inform, influence, entertain or sell) *0. Not at all* | *6. Very much*	0.67–6	Mean SD Range Cronbach's α * This variable was measured in wave 4. To give the respondents in wave 3 and 4 that dropped out before wave 3 a score on this variable, regression imputation was used	4.62* 0.84* 0.67–6	4.61* 0.88* 0.67–6	4.61 0.94 0.67–6 .83	4.60 0.96 0.67–6

Table 7 (continued)

Variable	Question wording	Range		Wave 2	Wave 3	Wave 4	Wave 5
Quantity of exposure	*Based on self-reported exposure to national newspapers and online news:* How many days in a typical week do you read the following printed newspapers? <RANDOMIZE ORDER OF ITEMS> a. De Telegraaf b. Algemeen Dagblad c. de Volkskrant d. NRC Handelsblad e. Trouw f. Het Financieele Dagblad g. Reformatorisch Dagblad h. Nederlands Dagblad How many days in a typical week do you use the following websites or apps for the news? <RANDOMIZE ORDER OF ITEMS> a. nu.nl b. nos.nl c. metronieuws.nl (Metro) d. telegraaf.nl (De Telegraaf) e. ad.nl (Algemeen Dagblad) f. vk.nl of volkskrant.nl (de Volkskrant) g. nrc.nl (NRC Handelsblad) h. trouw.nl i. fd.nl (Financieele Dagblad) j. rd.nl (Reformatorisch Dagblad) k. nd.nl (Nederlands Dagblad) 0. *0 days* 1. *1 day* 2. *2 days* 3. *3 days* 4. *4 days* 5. *5 days* 6. *6 days* 7. *7 days* *Exposure was combined with outlet scores on ChatGPT visibility from the content analysis with the formula:* $AmountChatGPTExposure_{r,t} = ln \sum_{i=1}^{n} OutletUse_{i,r} * OutletAttention_{i,t}$	0–6.61	Mean	3.86	3.50	4.08	3.98
			SD	1.79	1.67	1.78	1.81
			Range	0–6.52	0–6.22	0–6.61	0–6.58
Knowledge of ChatGPT	Have you heard of ChatGPT before? 1. *No, I have never heard of it* 2. *Yes, I have heard of it but did not try it* 3. *Yes, I have already tried it once or a couple of times* 4. *Yes, I have used it regularly* *Recoded into a dummy of whether respondents have at least heard about ChatGPT*	0–1	Mean	.56	.73	.84	.88
			SD	.50	.44	.36	.33
			Range	0–1	0–1	0–1	0–1
Size of impact	ChatGPT will … *1. … have no effect on society at all* | *7. … have a large effect on society*	1–7	Mean	4.83	5.17	5.09	5.11
			SD	1.29	1.27	1.23	1.22
			Range	1–7	1–7	1–7	1–7
Valence of impact	ChatGPT will … *1. … make society worse* | *7. … make society better*	1–7	Mean	3.58	3.32	3.54	3.59
			SD	1.35	1.36	1.41	1.33
			Range	1–7	1–7	1–7	1–7

Table 8 Logistic regression models predicting learning about ChatGPT

	Model 1	Model 2	Model 4
Constant	0.25*** (0.06)	−2.08*** (0.39)	−2.26*** (0.40)
Wave 3	−0.75*** (0.11)	−0.47*** (0.12)	−0.42*** (0.12)
Wave 4	−0.70*** (0.15)	−0.23 (0.16)	−0.22 (0.16)
Wave 5	−1.22*** (0.21)	−0.62** (0.22)	−0.62** (0.22)
Age		< 0.01 (< 0.01)	< 0.01 (< 0.01)
Gender = female		0.52*** (0.10)	0.52*** (0.10)
Education = low		−0.37** (0.12)	−0.33** (0.12)
Education = high		0.99*** (0.12)	0.92*** (0.12)
Television news exposure		0.01 (0.01)	< 0.01 (0.01)
YouTube use		0.03 (0.03)	0.03 (0.03)
Twitter use		0.15*** (0.04)	0.14*** (0.04)
Tiktok use		−0.09 (0.05)	−0.10+ (0.05)
Technology optimism		0.03 (0.04)	0.01 (0.04)
Digital media literacy		0.31*** (0.06)	0.30*** (0.06)
Quantity weighted exposure			0.10*** (0.03)
χ^2	82.34***	339.11***	353.24***
-2 log likelihood	2741.70	2484.93	2470.80
Nagelkerke R^2	0.05	0.20	0.21
Cox & Snell R^2	0.04	0.15	0.16

Entries are logistic regression coefficients with standard errors in parentheses $N_{observations} = 2039$; $N_{respondents} = 1212$

$^{***}p < .001$. $^{**}p < .01$. $^{*}p < .05$

Table 9 Mixed regression models predicting perceived impact ChatGPT

Variable	Model 1	Model 2	Model 3
Fixed effects			
Constant	0.35*** (0.07)	0.15 (0.11)	0.15 (0.11)
Lag impact size	0.51*** (0.03)	0.52*** (0.02)	0.52*** (0.02)
Wave	−0.09*** (0.02)	−0.10*** (0.02)	−0.10*** (0.02)
Age		< 0.01 *** (< 0.01)	< 0.01 *** (< 0.01)
Gender = female		0.13 (0.04)	0.13 (0.04)
Education = low		0.06 (0.06)	0.07 (0.06)
Education = high		−0.08 (0.04)	−0.08 (0.04)
Television news exposure		0.02 (0.02)	0.02 (0.02)
YouTube use		0.01 (0.02)	0.01 (0.02)
Twitter use		−0.00 (0.02)	−0.00 (0.02)
Tiktok use		0.02 (0.03)	0.02 (0.03)
Technology optimism		0.04 (0.02)	0.04 (0.02)
Digital media literacy		−0.02 (0.02)	−0.02 (0.02)
Absolute sentiment			< -0.01 (0.02)
Random effects			
ID (Constant)	0.10 (0.07)	0.08 (0.06)	0.08 (0.06)
Residual variance	0.59 (0.08)	0.06 (0.08)	0.06 (0.08)
AR(1)	−0.29 (0.06)	−0.31 (0.06)	−0.31 (0.06)
Model fit statistics			
Log Pseudolikelihood	−2352.90	−2332.89	2332.89
Wald $\chi^2(2)$	455.55***	624.12***	629.46***

Note. Al variables in the models are standardized. Entries of the fixed effect models are regression coefficients with standard errors in parentheses. $N_{observations} = 1916$; $N_{groups} = 843$

$^{***}p < .001$. $^{**}p < .01$. $^{*}p < .05$

Table 10 Mixed regression models predicting perceived impact ChatGPT

Variable	Model 1	Model 2	Model 3
Fixed effects			
Constant	0.35*** (0.07)	0.15 (0.11)	0.10 (0.12)
Lag impact size	0.51*** (0.02)	0.52*** (0.02)	0.51*** (0.02)
Wave	−0.09 *** (0.02)	−0.10*** (0.02)	−0.08*** (0.03)
Age		< 0.01*** (< 0.01)	< 0.01*** (< 0.01)
Gender = female		0.13*** (0.04)	0.13*** (0.04)
Education = low		0.02 (0.06)	0.02 (0.06)
Education = high		−0.08 (0.04)	−0.09 (0.04)
Television news exposure		0.02 (0.02)	0.02 (0.02)
YouTube use		0.01 (0.02)	0.01 (0.02)
Twitter use		< 0.01 (0.02)	< 0.01 (0.02)
Tiktok use		< −0.01 (0.03)	< −0.01 (0.03)
Technology optimism		0.04 (0.02)	0.04 (0.02)
Digital media literacy		−0.01 (0.02)	−0.01 (0.02)
Strong impact			−0.06 (0.06)
Weak impact			0.09 (0.06)
Random effects			
ID (Constant)	0.10 (0.07)	0.08 (0.06)	0.09 (0.06)
Residual variance	0.59 (0.08)	0.06 (0.08)	0.59 (0.08)
AR(1)	−0.29 (0.06)	−0.31 (0.06)	−0.30 (0.06)
Model fit statistics			
Log Pseudolikelihood	2352.90	−2332.89	−2331.84
Wald $\chi^2(2)$	455.55***	624.12***	616.34***

Note. Al variables in the models are standardized. Entries of the fixed effect models are regression coefficients with standard errors in parentheses. $N_{observations} = 1916$; $N_{groups} = 843$

***$p < .001$. **$p < .01$. *$p < .05$

Table 11 Mixed regression models predicting valence regarding impact ChatGPT

Variable	Model 1	Model 2	Model 3
Fixed effects			
Constant	−0.17* (0.07)	0.03 (0.09)	0.03 (0.10)
Lag impact size	0.75*** (0.02)	0.65*** (0.02)	0.65*** (0.02)
Wave	0.07*** (0.02)	0.08*** (0.02)	0.09*** (0.02)
Age		< −0.01** (< 0.01)	< −0.01** (< 0.01)
Gender = female		− < 0.01 (0.03)	−0.01 (0.03)
Education = low		−0.12** (0.05)	−0.12** (0.05)
Education = high		0.03** (0.04)	0.03** (0.04)
Television news exposure		0.05** (0.02)	0.04* (0.02)
YouTube use		0.01 (0.02)	0.01 (0.02)
Twitter use		0.01 (0.02)	0.01 (0.02)
Tiktok use		−0.03 (0.02)	−0.03 (0.02)
Technology optimism		0.13*** (0.02)	0.13*** (0.02)
Digital media literacy		− < 0.01 (0.02)	− < 0.01 (0.02)
Negative news			−0.01 (0.04)
Neutral news			−0.01 (0.03)
Positive news			0.04 (0.03)
Random effects			
ID (Constant)	< 0.01 (< 0.01)	0.01 (0.03)	0.01 (0.03)
Residual variance	0.68 (3.44)	0.62 0.05)	0.62 0.05)
AR(1)	−0.38 (4.69)	−0.36 (0.05)	−0.36 (0.05)
Model fit statistics			
Log Pseudolikelihood	2272.97	−2222.33	−2220.16
Wald $\chi^2(2)$	1529.69***	1872.24	1929.99

Note. Al variables in the models are standardized. Entries of the fixed effect models are regression coefficients with standard errors in parentheses. $N_{observations} = 1916$; $N_{groups} = 843$

***$p < .001$. **$p < .01$. *$p < .05$

Curmudgeon Corner Curmudgeon Corner is a short opinionated column on trends in technology, arts, science and society, commenting on issues of concern to the research community and wider society. Whilst the drive for super-human intelligence promotes potential benefits to wider society, it also raises deep concerns of existential risk, thereby highlighting the need for an ongoing conversation between technology and society. At the core of Curmudgeon concern is the question: What is it to be human in the age of the AI machine? -Editor.

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Data availability As the survey data is part of a collaborative survey, we are unable to make the data available at this time. The survey data will be released on OSF on January 1, 2026.

Declarations

Conflict of interest The authors declare no competing interests.

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