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A Health Crisis in the Age of Misinformation: How Social Media and Mass Media Influenced Misperceptions about COVID-19 and Compliance Behavior

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ABSTRACT

The media are important information disseminators in society. Particularly in uncertain times, such as the COVID-19 pandemic, citizens are very "media dependent." The way in which people are informed about the coronavirus heavily depends on the type of media they use. Especially on social media, the share of misinformation is considerable, which might impact the way in which people comply with preventive measures. Our study investigates how media use affects misperceptions about the coronavirus and whether this influences important behavioral determinants as well as compliance behavior itself. The results of a unique 5-wave panel survey (N = 1,741) conducted between April 2020 and October 2020 show that the use of mass media reduces misperceptions. The same was found for *Twitter* users, whereas *Facebook* and *Instagram* users have *more* misperceptions about the coronavirus. Misperceptions negatively influence the perceived severity, susceptibility and efficacy of preventive measures taken by governments, which may ultimately result in decreased compliance. Our findings underline the important role of media consumption and misperceptions in shaping citizens' beliefs and behavior regarding COVID-19. They re-emphasize the importance of mass media, such as newspapers, television broadcasts or reliable news websites, to inform the public about current affairs. They also imply that platform media might be more heterogeneous in their effects than mass media.

When the coronavirus rapidly spread across the globe in the spring of 2020, one country after another implemented a wide-ranging set of measures to contain the COVID-19 pandemic (Lazarus et al., 2020). In the Netherlands, schools, shops, and restaurants were closed, and people were asked to work from home while maintaining social distance (Rijksoverheid, 2020). During this first wave of the pandemic many people adhered to the recommendations made by the government (RIVM, 2022). However, as the pandemic continued, obeying the measures became increasingly challenging for many people, and adherence to several measures gradually declined during the spring and summer of 2021 (RIVM, 2022), even though most people were not vaccinated by that time (Corona Dashboard, 2022). For example, in May 2021, only 55.6% of those with COVID-19-related symptoms stayed at home (as recommended), and 65.3% kept sufficient distance from other people (RIVM, 2021). In the Netherlands, COVID-19 measures were mostly announced during press conferences (Antonides & Van Leeuwen, 2021), which were broadcast on national TV. While most people used traditional *mass media* (i.e., television news broadcasts, newspapers, and websites from traditional news organizations that comply with journalistic standards) and television in particular to inform themselves about COVID-19, *online platforms* such as social media and online forums also served as an information source (Te Poel, Linn, Baumgartner, van Dijk, & Smit, 2021) and were used to share COVID-19-related (mis)information (Gupta et al., 2020). In contrast to mass media, social media also accounted for a broad dissemination of conspiracy theories, rumors and other sorts of misinformation about the virus (Tasnim, Hossain, & Mazumder, 2020). This is worrisome because belief in these conspiracy theories can lead to negative attitudes toward COVID-19-related government responses (Georgiou, Delfabbro, & Balzan, 2020) and can reduce people's willingness to comply with preventive measures (Allington, Duffy, Wessely, Dhavan, & Rubin, 2020; Roozenbeek et al., 2020).

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Our study aims to investigate whether the consumption of different media influences misperceptions about the coronavirus and whether these misperceptions affect compliance with COVID-19 measures. The Dutch context of this study particularly interesting because the government opted for a less stringent lockdown approach: A so-called "intelligent lockdown" (see Yerkes et al., 2020) was imposed that emphasized the individual responsibility of citizens rather than state enforcement; hence, the role of media—rather than law and legislation—to guide citizens' behavior was even more crucial.

Media Use and Misperceptions about COVID-19

Media play a central role in the dissemination of information, particularly in ambiguous times of crisis when people are more "media dependent" (Ball-Rokeach & DeFleur, 1976; Boukes, Damstra, & Vliegenthart, 2021). Even—or especially—in a time often labeled the "post-truth" era, journalists still aspire to report factually, and the journalistic search for credibility is still their main priority (McNair, 2017). Thus, the consumption of regular news has throughout the years been demonstrated to be an important predictor of obtaining information about current affairs (e.g., Beckers, Van Aelst, Verhoest, & d'Haenens, 2020; Price & Zaller, 1993). According to Nielsen, Fletcher, Newman, Brennen, and Howard (2020), people consumed more news during the COVID-19 pandemic, and many people (i.e., especially those with lower levels of education) relied on the news media to be informed about the coronavirus; importantly, they considered this a trustworthy source. News consumption also increased knowledge about COVID-19 and people reported that the news media helped them to understand the COVID-19 crisis and what they could do to stay safe and protect themselves (Nielsen et al., 2020).

The COVID-19 pandemic has been called an infodemic by the World Health Organization due to the large amount of information *and* misinformation that was available (Wang, Li, Hutch, Naidech, & Luo, 2021; Zarocostas, 2020). Health-related misinformation can be defined as "science and health misinformation as information that is contrary to the epistemic consensus of the scientific community regarding a phenomenon" (Swire-Thompson & Lazer, 2020). Thus, all information about COVID-19 that was never supported by scientific evidence—such as the idea that coronavirus was purposely created—can be classified as misinformation (Ecker et al., 2022). However, the definition also accounts for the fact that scientific knowledge is constantly evolving and that what is considered true and false might change over time as new evidence is found (Swire-Thompson & Lazer, 2020). Especially in the beginning of the pandemic, communication about the coronavirus was challenging due to the high levels of uncertainty induced by limited (scientific) knowledge about the virus (Finset et al., 2020). At the time, real facts were sparse, and recommendations based on the *best evidence at the time* were subject to change (Eysenbach, 2020). One example of a rapidly refuted insight was the presumed effectiveness of *hydroxychloroquine* as a cure for COVID-19 (Saag, 2020).

By paying attention to such topics—even when stating that these are false—journalistic media may amplify the visibility, reach and potential impact of misinformation (e.g., Bruns, Harrington, & Hurcombe, 2021). In contrast to these mass media, which are likely to correct or fact-check misinformation once new information comes to light (Lwin, Lee, Panchapakesan, & Tandoc, 2021), platform media facilitate the sharing of news articles without these being checked for accuracy against current journalistic standards or medical evidence. Although corrective social media responses that are accompanied by a trustworthy source may be effective in correcting misperceptions (Vraga & Bode, 2018), most information on these platforms originates from peers and laypeople without the skills or professional duty to circulate factually correct information or fact-check incorrect information.

It has been shown that platform media (or social media) in particular played an important role in the dissemination of misinformation about COVID-19 (e.g., Scannell et al., 2021). However, exposure to inaccurate information alone does not automatically result in misperceptions. According to Ecker et al. (2022), different cognitive and socioaffective factors are associated with the formation of misperceptions or false beliefs. It could be assumed that these factors are amplified by platform media relative to traditional media. A first cognitive factor relates to the *illusionary truth effect*, whereby repetition makes a claim more believable (Van der Linden, 2022). As platform media support the spread of information within networks, it is likely that certain people encounter a certain claim multiple times: Falsehoods are shared more often and at a faster rate on social media than truths (Vosoughi, Roy, & Aral, 2018). This repetition strengthens belief formation, sometimes despite accurate prior knowledge or contradictory advice (Ecker et al., 2022). Other drivers of misperceptions include the fact that people generally tend to overlook cues about a message's source, and sources are naturally more trusted when they closely reflect people's own views (Ecker et al., 2022). Both factors are expected to be especially prevalent on platform media, and therefore, these media are more likely to cause misperceptions. This is confirmed by Bridgman et al. (2020), who showed that exposure to social media was related to misperceptions regarding basic facts about COVID-19, whereas news media use resulted in fewer misperceptions. Accordingly, we expect to find opposite effects for the consumption of mass media news vis-à-vis the effects of social media use:

Hypothesis 1a: *There is a positive relationship between platform media use and misperceptions about COVID-19.*

Hypothesis 1b: *There is a negative relationship between mass media use and misperceptions about COVID-19.*

Understanding the Influence of Misperceptions on Compliance from an EPPM Perspective

Believing false information about preventive COVID-19 measures can undermine citizens' compliance with such measures (e.g., Bridgman et al., 2020; Lee et al., 2020). The Extended Parallel Process Model (EPPM, Witte, 1992) has been widely used in studies to explain the effectiveness – and failure – of messages addressing health-related behavior change. According to the EPPM and other behavior change theories, such as the health belief model (Strecher & Rosenstock, 1997) and protection motivation theory (Floyd, Prentice-Dunn, & Rogers, 2000; Rogers, 1975), the variables perceived *severity*, perceived *susceptibility*, and perceived *efficacy of the proposed response* are critical prerequisites of behavior change. The first two variables, perceived severity (i.e., an individual's beliefs about the seriousness of the threat) and perceived susceptibility (i.e., an individual's beliefs about his or her chances about experiencing the threat) (see Witte, 1992), are crucial to convincing the message recipient of the threat associated with not performing the behavior.

With respect to COVID-19, this involves an estimation or evaluation of the risks associated with being infected with the coronavirus, whether the consequences will be severe, and whether infection is likely to happen at all. The latter variable, perceived *response efficacy*, refers to an individual's belief as to whether a response effectively prevents the threat (see Witte, 1992). Thus, even when people are convinced of a health risk, they will only be motivated to comply with preventive measures if they find the proposed measures effective. The importance of severity, susceptibility, and efficacy as antecedents of compliance behavior has been supported in many health domains, including COVID-19 (e.g., Floyd et al., 2000; Kowalski & Black, 2021; Nazione, Perrault, & Pace, 2021). Therefore, we expect that an individual's perceptions of severity, susceptibility and response efficacy with respect to COVID-19 and the governmental measures taken will be positively associated with compliance with such measures.

A few studies have investigated the relationship between COVID-19-related media use and EPPM variables and found conflicting results (Gardikiotis et al., 2021; Nazione et al., 2021). However, the impact of specific rumors – or misinformation – was not investigated. A Canadian study did consider misperceptions and found that they are associated with reduced COVID-19 risk perceptions as well as lower compliance with social distancing measures (Bridgman et al., 2020). It can be argued that *mis*information affects severity, susceptibility and response efficacy differently. For example, stories about COVID-19 being caused by 5G technology have spread widely. If this is believed to be true, social distancing or hygiene measures could appear useless, resulting in low perceived *response efficacy.* After all, if the disease were caused by 5G technology, social distancing would be useless. Alternatively, the idea that only older people are at risk of severe illness from the virus could easily decrease the *perceived susceptibility* of COVID-19 among younger age cohorts. Regular news media, in contrast, have often produced news items that correct these misbeliefs. Therefore, we argue that misperceptions about COVID-19 can undermine the variables that encourage compliance.

Hypothesis 2: *Misperceptions about COVID-19 negatively affect severity, susceptibility, and efficacy perceptions.*

Hypothesis 3: *Perceived severity (a), susceptibility (b) and efficacy (c) positively influence compliance with COVID-19 measures.*

Materials and Methods

Our data were collected as part of a larger 5-wave panel online survey conducted on a representative sample in the Netherlands (Bakker, van der Wal, & Vliegenthart, 2020; Ethics Review Board number: 2020-CS-12107). All questionnaires and accompanying datasets are available at OSF (https://osf.io/kwz7a/). The first four waves were conducted at approximately 3-week intervals starting April 10 (wave 1); April 30 (wave 2); May 25 (wave 3) and June 29, 2020 (wave 4). The fifth wave was conducted after the summer holidays starting on September 10, 2020.

Sample

The sample was recruited by I&O Research, an ISO certified panel administration company based in the Netherlands. Panel members were approached by e-mail with a link to the online survey. In the first wave, 3,750 invitations were sent, out of which 1,741 led to valid participation (initial response rate of 46.45%). In this wave, 50.9% of the participants identified as female and 49.1% identified as male. Approximately one-third (31.5%) were aged between 18 and 39, 44.3% were aged between 40 and 64, and 24.4% were 65 years of age or older. Education levels were distributed as follows: 22.3% (low), 39.6% (moderate) and 38.1% (high). The sample was representative of the Dutch population and did not remarkably change in terms of composition in the subsequent waves. Accordingly, the data were not weighted in the analyses. See Table A1 for an overview of the sample composition per wave. Dropout rates were the highest between waves 1 and 2 (277 respondents, i.e., 18%). Although this attrition rate might seem substantial, it is comparable to or less than those reported in previous studies using different pollsters and contexts (e.g., Boomgaarden, Van Spanje, Vliegenthart, & De Vreese, 2011; Boukes, Damstra & Vliegenthart, 2021). Wave 2 had 1,464 participants, wave 3 had 1,255 participants, 1,049 participated in wave 4 and 904 participated in the last wave (wave 5). Panel mortality did not lead to significant differences in education levels ($M_{dropouts}$ = 4.79, SD = 1.54, $M_{participants}$ = 4.72, SD = 1.49; t = 1.02, p =.35), but participants in higher age groups ($M_{dropouts}$ = 1.88, SD =.72, $M_{participants}$ = 1.97, SD =.76; t = −2.42, p =.02) and men ($M_{dropouts}$ = 1.54, SD =.50, $M_{participants}$ = 1.47, SD =.50; t = 2.57, p =.01) were slightly less likely to drop out.

Measures

Mass media use (TV/newspapers/websites) was indicated by the mean score for the following question: Last week, how often did you view the following TV shows/read the following newspapers/ use the following news websites? The selected news outlets cover the most prominent news shows - both public and commercial broadcasts and hard news versus softer news - on Dutch national TV (*RTL Nieuws, NOS Journaal, Hart van Nederland, Editie NL, Nieuwsuur, EenVandaag, and "other TV news")*; major national newspapers varying in terms of left-wing and right-wing orientation (*De Telegraaf, NRC Handelsblad, Algemeen Dagblad, Trouw, De Volkskrant, Financieel Dagblad, and "regional newspaper")*; and major national Dutch news websites *NOS.nl, rtlnieuws.nl*, and *nu.nl*. For each outlet, respondents indicated how often they used the specific outlet on a scale from 1 to 8 (1 = never; 8 = 7 days a week) (M = 2.22, $SD_{between}$ = 0.72, SD_{within} = 0.27).[1]

Platform media use was measured using four items. For each of the platform media outlets, *Facebook, Twitter, Instagram*,

[1] Alternatively, a composite score could be made using the sufficient conditions approach, whereby mass media use is based on the most used medium. For instance, a person watching the NOS news broadcast every day and using no other mass media outlets would score 8 on such a measure, whereas on the average index this person would score 1.39. Rerunning our analyses using this alternative measure did not impact our substantive conclusions.

and *WhatsApp*, respondents answered the following question: Last week, how often did you use the following website or app? Response categories ranged from 1 (0 days) to 8 (7 days) (M = 3.72, $SD_{between}$ = 1.61, SD_{within} = 0.50).

Misperceptions were measured with three separate items referring to misinformation present on Dutch social media in the beginning of the pandemic, prior to the data collection of wave 1: A vaccine against COVID-19 is available but being kept secret by major pharmaceutical companies (M = 1.94, $SD_{between}$ = 1.25, SD_{within} = 0.49); COVID-19 is caused by 5G technology (M = 1.30, $SD_{between}$ =.83, SD_{within} = 0.49); and Only older people get severely ill from COVID-19 (M = 1.79, $SD_{between}$ = 1.05, SD_{within} = 0.98). Answer options ranged from 1 (totally disagree) to 7 (totally agree), and the items were analyzed separately. The correlation coefficients between the misperceptions were stable over time, with the strongest (moderate) correlation being between the misperception about the vaccines and the misperception of 5G technology (all waves r = .34, p's <.001) and the weakest correlation between the misperception about 5G technology and the one about older people (all waves r = .08-.18, p's <.01).

Perceived severity was measured using the following items: "The coronavirus is severe" and "the coronavirus is serious" (1 = *totally disagree*, 7 = *totally agree*) (M = 6.34, $SD_{between}$ =.96, SD_{within} =.14. α all waves > 0.88).

Perceived susceptibility was measured with the single item "I am afraid to die from the coronavirus" (1 = *totally disagree*, 7 = *totally agree*) (M = 2.19, $SD_{between}$ = 1.53, SD_{within} = 0.82).

Perceived efficacy was assessed for four behaviors, which cover the main behavioral recommendations made by the Dutch government to contain the pandemic (e.g., Antonides & van Leeuwen, 2021; RIVM, 2022) during the full time of data collection (i.e., keeping 1.5 meters distance from others; washing one's hands regularly for 20 seconds; and coughing and sneezing in one's elbow pit) and in the first few months of the pandemic (i.e., staying at home as much as possible). It should be noted that another effective measure, mask wearing, was not recommended by the government until early October 2020 (Rijksoverheid, 2020), after our data collection. Respondents answered the following question: "To what extent do you believe that the following measures are effective at protecting yourself and others from the coronavirus?" (1 = *not effective at all*, 7 = *very effective*) (M = 5.85, $SD_{between}$ = 0.91, SD_{within} = 0.53, α all waves > 0.71).

Compliance

Compliance was measured using a mean score of the following questions: "Which of the following recommendations did you comply with last week?" (a) Keeping 1.5 meters distance from others; (b) Staying at home as much as possible; (c) Washing your hands regularly for 20 seconds; and (d) Coughing and sneezing in your elbow pit. (0 = no, 1 = yes; range 0–1) (M =.82, $SD_{between}$ =.19, SD_{within} =.14).

Results

Statistical Analysis

To test our expectations, we use a random effects panel model using the xtreg package of the statistical software package STATA/SE 16.1. A panel model makes optimal use of the repeated measurement of our variables. Whereas cross-sectional datasets only allow us to draw conclusions about correlations between the variables of interest, the repeated measurement of these same variables gives us the opportunity to study the *dynamics of change* (Gujarati & Porter, 2003). This is possible because we cannot only draw from the heterogeneity (variance) between individuals, as we can in cross-sectional data, but we can also capitalize on the heterogeneity within individuals (i.e., changes over time). We can estimate whether a change in an individual on one variable affects the change in the same individual on another variable. In a practical sense, we first stack the data in such a way that each respondent is included in the dataset for as many waves as they responded to the invitation to participate. In other words, the dataset is reordered from wide to long. In a next step, we run a regression model over this long dataset. In a simplified sense, we regress the dependent variable as measured in all waves at once on the independent variables as measured in all waves at once. Specifically, we use a random effects panel data model. A random effects model (as opposed to a fixed effects model) allows modeling the impact of time-variant (e.g., mass media and platform media use) as well as time-invariant (e.g., social demographics) independent variables on our dependent variables.[2] An alternative approach to model this type of data is a lagged-dependent variable model, often used when only two waves of data are available. In addition, it overestimates the model fit due to autocorrelation, and it reduces the interpretability of time invariant factors, because much of the variance they explain is explained by the lagged dependent variable. We use listwise deletion per wave meaning that observations in one wave are removed when one of the variables in that wave had a missing value.[3]

Hypothesis Testing

Hypothesis 1a and H_{1b} were tested in three different models with one for each misperception. The unstandardized regression coefficients are presented in Table 1. We only find support for H_{1a}, which predicted a positive relationship between platform media use and misperceptions about COVID-19, for one of the three misperceptions, namely, that a vaccine is available (b = 0.038, SE = 0.014, p =.008). We find more support for H_{1b}, as the results show a negative relationship between mass media use and two misperceptions. Respondents using more mass media are less likely to believe that a vaccine is already available (b = −0.066, SE = 0.029, p = .024) and that only the elderly get severely ill from COVID-19 (b = −0.066, SE = 0.031, p = .032). Mass media use does not influence the belief that COVID-19 is caused by 5G technology (b = 0.027, SE = 0.020, p = .176). Notably, these effects of media use are rather small compared to the influence of some demographic variables. For example, the most significant

[2]The coefficients in the random effects models include both within-individual (over time) and between-individual effects.

[3]We chose to run the regression with unweighted data because frequency weights can bias the inferential table. To correct for heteroskedasticity, we used the variables we would have used for weights as control variables.

Table 1. Impact of media use on misperceptions

VARIABLES	(1) Vaccine is available	(2) Pandemic result of 5G	(3) Only elderly get sick
Mass media	−0.066*	0.027	−0.066*
	(0.029)	(0.020)	(0.031)
Platform media	0.038**	−0.003	0.018
	(0.014)	(0.010)	(0.014)
Female	0.078	0.088*	−0.152**
	(0.057)	(0.040)	(0.049)
Age = 40–64	−0.321***	−0.138**	−0.143*
	(0.070)	(0.048)	(0.060)
Age = 65+	−0.430***	−0.162**	0.161*
	(0.086)	(0.059)	(0.075)
Education	−0.220***	−0.093***	−0.044*
	(0.021)	(0.014)	(0.018)
Income level 1[1]	−0.144	0.040	−0.096
	(0.101)	(0.070)	(0.086)
Income level 2[1]	−0.042	0.057	0.003
	(0.106)	(0.073)	(0.090)
Income level 3[1]	−0.305**	−0.098	−0.144
	(0.099)	(0.068)	(0.083)
Income level 4[1]	−0.411***	−0.123	−0.233**
	(0.092)	(0.063)	(0.078)
Income level 5[1]	−0.490***	−0.171*	−0.215*
	(0.107)	(0.074)	(0.091)
Constant	3.397***	1.748***	2.455***
	(0.180)	(0.124)	(0.158)
R^2_{within}	0.001	0.001	0.001
$R^2_{between}$	0.123	0.053	0.033
$R^2_{overall}$	0.089	0.039	0.018
sigma_u	1.048	0.729	0.735
sigma_e	0.845	0.571	1.151
rho (ρ)	0.606	0.620	0.290
Observations	6,391	6,391	6,391
Number of *i*	1,740	1,740	1,740

Note: Cell entries are unstandardized regression coefficients; Standard errors in parentheses; *** p < 0.001, ** p < 0.01, * p < 0.05. [1] No answer is the reference category.

effect found for (b = −0.066, SE = 0.029, p =.024) means that using only mass media seven days a week would only decrease less than half of an item step in believing that a vaccine is available, which is measured on a seven-point scale. Similarly, the positive impact of using only platform media seven days a week would only increase the same misperception with a third point on the 7-point scale. Some background characteristics have an impact of a similar magnitude, such as being in the highest as opposed to the lowest age group (b = −0.430, SE = 0.086, p <.001) or being in the highest income category as opposed to not disclosing one's income (b = −0.490, SE = 0.107, p <.001). In general, sociodemographics explain more about the variation of the dependent variables than media use does. For example, females are more likely to believe that the pandemic was caused by 5G technology than males (b = 0.088, SE = 0.040 p = .026), whereas females are less prone to the misperception that only elderly individuals become severely ill (b = −0.152, SE = 0.049, p =.002). Furthermore, compared to the youngest age group (< 40 years), our results show that participants over the age of 65 are less likely to hold the misperceptions about 5G technology (b = −0.162, SE = 0.059, p =.006), but they are more likely to believe that only older people can get sick (b = 0.160, SE = 0.075, p = 032). Of the background characteristics, only income significantly impacts all three misperceptions. Because of the central role of background characteristics in explaining misperceptions, our models mostly explain variance between individuals ($R^2_{between\_vaccine}$ = 0.123; $R^2_{between\_5G}$ = 0.053; $R^2_{between\_elderly}$ = 0.033) and very little to no variation within individuals ($R^2_{within\_vaccine}$ = 0.001; $R^2_{within\_5G}$ = 0.001; $R^2_{within\_elderly}$ = 0.001).

In a next step, we test whether misperceptions negatively affect severity, susceptibility, and efficacy perceptions (H2) using the same analytical method: random effects panel data models. When controlling for social demographics and platform and mass media use, misperceptions still affect severity, susceptibility, and efficacy perceptions, although their impact is not universal (see Table 2). As expected, the misbeliefs have different effects on different perceptions. Respondents with a stronger belief in the premise that a vaccine is already available perceive the proposed response (i.e., the advised preventive behaviors) to be less efficacious (b = −0.045, SE = 0.009, p <.001) and perceive COVID-19 as less severe (b = −0.085, SE = 0.012, p <.001), while at the same time, they think that they are more susceptible to the virus (b = 0.034, SE = 0.015, p =.021). The misbelief about 5G technology does not impact perceived efficacy (b = −0.013, SE = 0.014, p =.349), but having this misperception does increase perceived susceptibility (b = 0.049, SE = 0.022, p =.024) and decreases perceived severity (b = −0.088, SE = 0.018, p <.001). Believing that only the elderly get severely ill negatively influences perceived efficacy (b = −0.048, SE = 0.007, p <.001), severity (b = −0.083, SE = 0.010, p <.001), and susceptibility (b = −0.027, SE = 0.011, p =.017). Hypothesis 2 thus finds sufficient support in our data, although the support is stronger for specific misperceptions than for others. Again, however, the effects are small: the largest effect size – the impact of the misperception that the pandemic is caused by 5G technology (b = −0.088) – suggests

Table 2. Impact of misperceptions on severity, susceptibility and efficiency

VARIABLES	(1) Efficacy	(2) Severity	(3) Susceptibility
Vaccine is available	−0.045***	−0.086***	0.034*
	(0.009)	(0.012)	(0.015)
Pandemic result of 5G	−0.013	−0.088***	0.049*
	(0.014)	(0.018)	(0.022)
Only elderly get sick	−0.048***	−0.083***	−0.027*
	(0.007)	(0.010)	(0.011)
Female	0.401***	0.224***	0.279***
	(0.041)	(0.042)	(0.071)
Age = 40–64	0.213***	0.159**	0.181*
	(0.050)	(0.052)	(0.086)
Age = 65+	0.308***	0.355***	0.354***
	(0.061)	(0.064)	(0.106)
Education	−0.015	−0.026	−0.107***
	(0.015)	(0.015)	(0.026)
Mass media	0.252***	0.193***	0.328***
	(0.021)	(0.026)	(0.034)
Platform media	0.006	−0.009	0.010
	(0.010)	(0.012)	(0.017)
Income level 1[1]	−0.227**	−0.124	−0.185
	(0.072)	(0.074)	(0.126)
Income level 2[1]	−0.104	0.010	−0.210
	(0.075)	(0.077)	(0.131)
Income level 3[1]	−0.057	−0.139	−0.246*
	(0.070)	(0.072)	(0.122)
Income level 4[1]	−0.149*	−0.072	−0.417***
	(0.065)	(0.067)	(0.114)
Income level 5[1]	0.010	−0.025	−0.354**
	(0.075)	(0.078)	(0.133)
Constant	4.854***	6.072***	1.555***
	(0.134)	(0.144)	(0.230)
R^2_{within}	0.022	0.011	0.011
R^2_{between}	0.170	0.170	0.105
R^2_{overall}	0.133	0.106	0.079
sigma_u	0.723	0.667	1.320
sigma_e	0.611	0.881	0.952
rho (ρ)	0.583	0.364	0.658
Observations	6,189	6,336	6,391
Number of i	1,725	1,738	1,740

Note: Cell entries are unstandardized regression coefficients; Standard errors in parentheses; *** p < 0.001, ** p < 0.01, * p < 0.05. [1] No answer is the reference category.

that the difference between the lowest value on this scale (*1 = this is not true*) and the highest value (*7 = completely true*) would decrease perceived severity by half a point on the 7-point scale. In these models, most of the variation that is explained is between individuals ($R^2_{between\_efficacy}$ = 0.170; $R^2_{between\_severity}$ = 0.170; $R^2_{between\_susceptibility}$ = 0.105), but our variables also explain some variation within individuals ($R^2_{within\_efficacy}$ = 0.022; $R^2_{within\_severity}$ = 0.011; $R^2_{within\_susceptibility}$ = 0.011). Most notably, by using more mass media (efficacy: b = 0.252, SE = 0.021, p <.001; severity: b = 0.193, SE = 0.026, p <.001; susceptibility: b = 0.328, SE = 0.034, p =.001) or having less misbeliefs, individuals can guide their efficacy, severity and susceptibility beliefs in the right direction.

Finally, the EPPM assumes that (a) perceived severity, (b) susceptibility and (c) efficacy positively influence compliance with COVID-19 measures (H_3), which we test in a final model presented in Table 3. All three perceptions increase compliance with COVID-19 measures, lending support for H_3. This may also mean that when misperceptions decrease perceived severity, susceptibility and efficacy, this may impede compliance with COVID-19 measures.

Possibly, the platform media included in our survey are not as homogeneous as the mass media outlets (see the Discussion section for a more detailed discussion). Therefore, we ran an exploratory analysis to determine whether the use of specific platform media might be more (or less) associated with misperceptions. The results of this model showed that *WhatsApp* was not associated with any misperception (see Table 4). *Twitter*, negatively impacted the misperception about pharmaceutical companies (b = −0.026, SE = 0.012, p =.036), thereby behaving similarly to mass media and in contrast to what we hypothesized about platform media generally. For the other two misperceptions, no significant relationship with *Twitter* use was observed. *Facebook* and *Instagram*, on the other hand, showed effects supporting H_{1a} for one misperception. *Facebook* usage increased the misperception about pharmaceutical companies (b = 0.028, SE = 0.008, p <.001), while *Instagram* use increased the misperception that only the elderly get severely ill (b = 0.019, SE = 0.010, p = .049).

Table 3. Impact of severity, susceptibility and efficiency on compliance

VARIABLES	(1) Compliance
Severity	0.012***
	(0.002)
Susceptibility	0.010***
	(0.002)
Efficacy	0.082***
	(0.003)
Female	0.039***
	(0.007)
Age = 40–64	−0.008
	(0.009)
Age = 65+	−0.009
	(0.010)
Education	0.002
	(0.003)
Income level 1[1]	−0.014
	(0.013)
Income level 2[1]	−0.038**
	(0.014)
Income level 3[1]	−0.007
	(0.013)
Income level 4[1]	−0.010
	(0.012)
Income level 5[1]	0.021
	(0.014)
Constant	0.189***
	(0.027)
R^2_{within}	0.073
$R^2_{between}$	0.335
$R^2_{overall}$	0.258
sigma_u	0.117
sigma_e	0.153
rho (ρ)	0.370
Observations	6,147
Number of *i*	1,721

Note: Cell entries are unstandardized regression coefficients; Standard errors in parentheses; *** p < 0.001, ** p < 0.01, * p < 0.05. [1] No answer is the reference category.

Discussion

Our study showed that, in general, mass media negatively impact misperceptions, thereby *preventing* the diffusion of misinformation within society. This is good news from the perspective that journalism is indispensable to a healthy society. Informing the public and helping citizens to correctly interpret current affairs are key principles for individual journalists (Coleman, Lee, Yaschur, Meader, & McElroy, 2018), and the consumption of their products thus indeed seems to decrease the intention to believe in these misperceptions. Overall, the use of platform media influenced the likelihood of believing in one of the COVID-19-related misperceptions. Closer inspection of the data revealed that different platform media impacted misperceptions differently. *Facebook* and *Instagram* use positively increased the likelihood of believing in one of the misperceptions, whereas using *Twitter* reduced the belief in one of the misperceptions. These findings align with previous research showing *Twitter* to positively affect the acquisition of current affairs knowledge more generally, while frequent *Facebook* usage causes a decline in knowledge acquisition (Boukes, 2019).

This differential effect of social media might be related to the different content that is offered on the platforms together with the motivations with which the audience uses them. *Twitter* timelines (or trending topics) often closely overlap with stories shared by the legacy news media (Kwak, Lee, Park, & Moon, 2010); moreover, the one-directional relationships of this platform (Davenport, Bergman, Bergman, & Fearrington, 2014) often reflect the normal relationships

Table 4. Impact of media use on misperceptions, platform media split out

VARIABLES	(1) Vaccine is available	(2) Pandemic result of 5G	(3) Only elderly get sick
Mass media	−0.063*	0.028	−0.067*
	(0.029)	(0.020)	(0.031)
Facebook	0.028***	0.006	0.008
	(0.008)	(0.005)	(0.008)
Twitter	−0.026*	−0.009	0.004
	(0.012)	(0.008)	(0.012)
Instagram	0.010	−0.004	0.019*
	(0.010)	(0.007)	(0.010)
WhatsApp	0.004	−0.002	−0.014
	(0.008)	(0.005)	(0.009)
Female	0.048	0.081*	−0.156**
	(0.058)	(0.040)	(0.050)
Age = 40–64	−0.321***	−0.142**	−0.129*
	(0.070)	(0.049)	(0.061)
Age = 65+	−0.436***	−0.168**	0.171*
	(0.086)	(0.059)	(0.076)
Education	−0.215***	−0.091***	−0.043*
	(0.021)	(0.014)	(0.018)
Income level 1[1]	−0.150	0.037	−0.103
	(0.101)	(0.070)	(0.086)
Income level 2[1]	−0.051	0.055	−0.001
	(0.105)	(0.073)	(0.090)
Income level 3[1]	−0.310**	−0.100	−0.144
	(0.098)	(0.068)	(0.083)
Income level 4[1]	−0.414***	−0.124	−0.227**
	(0.091)	(0.063)	(0.078)
Income level 5[1]	−0.486***	−0.170*	−0.203*
	(0.106)	(0.073)	(0.091)
Constant	3.432***	1.754***	2.516***
	(0.180)	(0.124)	(0.160)
R^2_{within}	0.000	0.000	0.002
$R^2_{between}$	0.134	0.057	0.034
$R^2_{overall}$	0.095	0.041	0.020
sigma_u	1.039	0.726	0.736
sigma_e	0.845	0.571	1.151
rho (ρ)	0.602	0.618	0.290
Observations	6,391	6,391	6,391
Number of *i*	1,740	1,740	1,740

Note: Cell entries are unstandardized regression coefficients; Standard errors in parentheses; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. [1] No answer is the reference category.

between a sender (often a news outlet, journalist, or politician) and receiver (a citizen). *Facebook*, in contrast, is built around reciprocal relationships (i.e., friending), and most citizens use it out of social motivations or for entertainment purposes (Ju, Jeong, & Chyi, 2014), just like *Instagram*. Accordingly, people will be exposed to reliable news sources more frequently on *Twitter* than on *Facebook* and *Instagram*, where they will mainly see (probably less reliable) messages from family, friends, and non-journalistic influencers (Wang, 2017). However, this effect might be contextual: In the U.S., for example, the *Twitter* discourse is much more polarized, and research has found that low-credibility content about COVID-19 is more prominent on *Twitter* timelines than on *Facebook* (Yang et al., 2021), which might explain why *Twitter* use in the U.S. is associated with misperceptions (Bridgman et al., 2020).

Furthermore, our study shows that misperceptions negatively influence the antecedents of compliance behavior, supporting earlier studies (Allington et al., 2020; Lee et al., 2020; Roozenbeek et al., 2020). We purposely included multiple misperceptions in our study with varying degrees of extremism, and all of them reduced perceived *severity*, indicating that people who hold misperceptions resulting from misinformation tend to underestimate the threat of COVID-19. Two out of three misperceptions increased perceived *susceptibility*, whereas perceived *efficacy* was reduced by two of them. Since misperceptions seem to intervene at different points of the process leading to compliance, depending on the specific misperception, health communication practitioners and policy-makers should take this into account when developing interventions to improve compliance behavior. This might apply not only to the preventive measures included in our study but also to interventions that encourage other behaviors, such as vaccine uptake.

One of the strengths of our study is that we used a five-wave panel survey to test our hypotheses. This allowed us to take into account unobserved individual heterogeneity and control for omitted variables that could explain relationships between our variables. Because of our analytical strategy, we are confident about the causal claims that we make. However, the time difference between the waves – three weeks, as determined by the larger data collection – does not match the theoretical expectations regarding mediation. Assuming a mediation would mean that a person sees a conspiracy theory at a point in time, and the effect of this exposure only and exactly materializes three weeks later, whereas this effect might occur within hours in reality. Future research should therefore formally test the full mediation effects suggested by our paper.

Our study has some limitations. First, since our study was part of a larger panel survey, we were restricted by the number of items we could measure our variables with. The variable perceived *susceptibility* was therefore not optimally measured. We used the item "I am afraid to die from the coronavirus" as an indicator, which does not capture less extreme feelings of susceptibility, such as the perceived risk of becoming ill, hospitalized, or getting long-haul COVID. Future research could have a closer look at this construct to provide a more nuanced account. Despite these drawbacks, we believe that "dying from corona" was a suitable indicator of perceived susceptibility, especially for the first six months of the pandemic. When our data were collected, no vaccine or treatment was available. Furthermore, we were unable to measure self-efficacy, which is also a predictor of compliance with COVID-19 regulations (Kowalski & Black, 2021; Nazione et al., 2021). We argue, however, that perceived *response efficacy* would be more important to include in our model, since it is more likely to be affected by misinformation. The importance of response efficacy in the context of COVID-19 has also been supported by other research (Hornik et al., 2021). Furthermore, support for misperceptions was limited. Particularly the 5G misperception was held by only a few people. Nevertheless, when these percentages are translated to a population level, this still means that 125,000 Dutch adults support such theory. Moreover, the result that a much larger part of the sample neither agrees nor disagrees with the misperceptions (the "doubters") is probably a reason for even greater concern. Our study shows that whereas mass media use prevents misperceptions, the use of *Facebook* and *Instagram* increases them. As misperceptions can be detrimental with respect to compliance behavior, this emphasizes the need for people to be properly informed. Especially in the Dutch context where the government emphasized citizens' individual responsibility, the role of the media should not be underestimated. It is therefore important that citizens do not only rely on social media to gather their news and keep using newspapers, television broadcasts or reliable news websites to learn about current affairs. In times of increasing news avoidance (Skovsgaard & Andersen, 2020), it is also in the interest of—and thus the responsibility of—governments and policy-makers that regular news media have a solid financial basis and reach a considerable share of the population.

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Table A1. Sample descriptives per wave

		Wave 1 April 10–21, 2020 $N = 1741$	Wave 2 April 30 – May 9, 2020 $N = 1464$	Wave 3 May 25 – June 3, 2020 $N = 1255$	Wave 4 June 29 – July 7, 2020 $N = 1049$	Wave 5 September 10–16, 2020 $N = 904$
		n (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)
Gender	Female	886 (50.9)	748 (51.1)	637 (50.8)	539 (49.3)	434 (48.0)
	Male	855 (49.1)	716 (48.9)	618 (49.2)	555 (50.7)	470 (52.0)
Age group	18–39	548 (31.5)	438 (29.9)	389 (31.0)	323 (29.5)	264 (29.2)
	40–64	772 (44.3)	647 (44.2)	536 (42.7)	468 (42.8)	380 (42.0)
	> 65	421 (24.2)	379 (25.9)	330 (26.3)	303 (27.7)	260 (28.8)
Education level	Low	388 (22.3)	340 (23.2)	286 (22.8)	252 (23.0)	210 (23.2)
	Middle	690 (39.6)	580 (39.6)	496 (39.5)	432 (39.5)	360 (39.8)
	High	663 (38.1)	544 (37.2)	473 (37.7)	410 (37.5)	334 (36.9)