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Article

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A longitudinal perspective on perceived vulnerability to disease during the COVID-19 pandemic in Belgium

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Summary

During the coronavirus disease 2019 pandemic, individuals relied heavily on media sources to stay informed about the disease and public health measures. However, differences exist in the type and frequency of news media consumption, which can be linked to their perceived vulnerability to disease. In this longitudinal study, 1000 Flemish (Belgium) individuals were followed from March 2020 until September 2020, focussing on the evolution in perceived vulnerability to disease (i.e. perceived infectability and germ aversion). Media consumption significantly impacts perceived germ aversion; heavy consumers of commercial media reported greater germ aversion than light consumers of these media. The evolution of germ aversion among individuals from March to August depends on their gender, living environment, age and possibility to work from home. Furthermore, the evolution of perceived infectability depends on the age and living environment of the respondent. These findings may interest policy makers and media professionals to anticipate how anxieties regarding contracting an infectious disease evolve over time and how individual characteristics affect this evolution.

Keywords: biostatistics, media, psychology, vulnerability to disease, longitudinal analysis

INTRODUCTION

Throughout 2020, the coronavirus disease 2019 (COVID-19) rapidly spread worldwide. To respond to this pandemic, many countries combined containment and reduction activities aimed at delaying major surges of patients and levelling the demand for hospital beds, while protecting the most vulnerable from infection (Bedford *et al.*, 2020; Molenberghs *et al.*, 2020a). Holmes *et al.* accurately identified the mental health impact of this pandemic as an important area of research going forward (Holmes *et al.*, 2020). The growing fear of disease, death and loss was associated with adverse physical and mental health consequences among individuals. At the same time, the prolonged social isolation and lockdown measures were exacerbating already existing vulnerabilities, like economic problems or loneliness (Arendt *et al.*, 2020; Brooks *et al.*, 2020; Généreux *et al.*, 2020; Holmes *et al.*, 2020). These lockdown measures also increased individuals' reliance on news media to inform them about the spread of the pandemic and new public health measures taken by policy makers (Frissen *et al.*, 2020). This growing reliance on legacy media and the growing penchant for social media with alternative messages also contributed to adverse mental health consequences (Garfin *et al.*, 2020). Several studies investigated the increased of levels of stress, fear and anxiety by comparing data from pre-COVID to data from during the COVID-19 pandemic. Davillas and Jones showed that the prevalence of psychological distress increased from 18 to 28% between 2018 and

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April 2020 (Davillas and Jones, 2020). Cross-sectional studies indicated that perceived vulnerability to disease was linked to various dynamics of adverse mental health and greater emotional distress during the pandemic—but conversely, also to greater adherence to public health measures (Boyraz *et al.*, 2020; Mallett *et al.*, 2021; Stangier *et al.*, 2021). Less evidence existed that charts the evolution of perceived vulnerability during the pandemic.

We used longitudinal data to model dynamics in perceived vulnerability to disease among a sample of the adult population of Flanders, the northern, Dutch-speaking region of Belgium, across the first 6 months of the COVID-19 pandemic (March to September 2020). We focussed on a number of potential modifiers of this evolution: media consumption and key sociodemographic characteristics like age and gender. This longitudinal approach was particularly relevant in the context of this crisis as data from a single time point fails to capture the dynamic nature of public health measures that were sometimes removed and reinstalled, of spikes and dips in reported infection and mortality rates, and of patterns of media consumption.

We expected differences by key sociodemographic characteristics, such as gender (De Coninck *et al.*, 2020a) and age (de Bruin, 2021). Galasso *et al.* conducted a two-wave panel study in eight OECD countries in March and April of 2020 and concluded that women were more likely than men to perceive the pandemic as a serious health problem, although the mortality rate of COVID-19 was higher among men (Galasso *et al.*, 2020; Molenberghs *et al.*, 2020b). The role of age was mixed: while some studies indicated that younger people experience adverse mental health outcomes (e.g. increased depression), others found that older people report greater perceived risk of dying following a COVID-19 infection (de Bruin, 2021). This was not entirely surprising as on the one hand lockdown measures hampered young people's daily lives by reducing their social contacts (e.g. through the cancellation of cultural events, working from home, etc.). On the other hand, the mortality rate of COVID-19 among older people was significantly higher than that of younger age groups (Molenberghs *et al.*, 2020b). Thus, as older age categories were aware that they are more at risk of infection and mortality due to COVID-19, it is understandable that their fear of the disease was greater than that of younger individuals. Recent studies also indicated that perceived vulnerability to disease differs depending on individuals' socioeconomic status (e.g. educational attainment, work status prior and during the pandemic): individuals with a high education and those who were able to work from home reported significantly lower vulnerability to disease than those with a low education or without the option to work from home (De Coninck *et al.*, 2020a).

Information about public health was disseminated through news media's almost non-stop coverage of the COVID-19 crisis: traditional (television, radio, newspapers) and social media are the main platforms for disseminating information (Frissen *et al.*, 2020; Merchant and Lurie, 2020). Particularly during the COVID-19 pandemic, people's reliance on traditional news media grew rapidly. Given the precarious public health situation in many countries, it was vital that news media convey accurate information. Further, the content of media coverage was also associated with mental health: previous research illustrated that sensationalized and tabloidized coverage of traumatic events (e.g. graphic imagery) was linked with greater stress. A content analysis of global media coverage of the COVID-19 pandemic by Ogbodo *et al.* (Ogbodo *et al.*, 2020) found that human interest and fearmongering frames were dominant. Not all media covered this crisis in the same way. Although the evidence of media effects in this crisis was scarce, analyses of the media consumption of coverage of previous traumatic events (like terrorist attacks) had shown that the consumption of sensationalized and tabloidized coverage—often found on commercial media or in popular newspapers—was related to higher stress among the public (Garfin *et al.*, 2020). For the COVID-19 pandemic, preliminary evidence showed that media consumption of both traditional and social media was linked to adverse mental health outcomes (i.e. greater stress, anxiety and depression) (He *et al.*, 2021; Neill *et al.*, 2021). However, information that distinguishes between the effects of different media types (public versus commercial media, quality versus popular newspapers) is currently lacking.

The present study contributed to the literature on the effects of the pandemic on perceived vulnerability. The longitudinal design that we adopted to chart the evolution of perceived vulnerability to disease throughout the first 6 months of COVID-19 had only scarcely been used in the context of this pandemic [for a notable exception, see (Kittel *et al.*, 2021)]. The panel data we collected at four points during the first 6 months of the pandemic in Flanders, Belgium, allowed us to track respondents over time and control for individual unobserved effects. Although various cross-sectional studies that investigated the mental health consequences of the pandemic on individuals had been conducted (Arendt *et al.*, 2020; Brooks *et al.*, 2020; Généreux *et al.*, 2020; Holmes *et al.*, 2020), these data did not allow for causal inferences. Similarly, several studies had been conducted which used a repeated cross-sectional design [e.g. see (Debowska *et al.*, 2020)]. Although these studies could provide relevant insights into trends

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at an aggregate level, they did not allow to track individual differences over time. Finally, when longitudinal studies were conducted during the crisis, they either compared the situation before and during the pandemic or conducted a two-wave panel study during the pandemic [see (Galasso *et al.*, 2020)]. Although these types of studies could provide valuable insights into the evolution of mental health indicators, most remained limited in their explanatory power of within-person changes over longer periods of time (for one exception for the Belgian context, see studies conducted using data from the Motivation Barometer, https://motivationbarometer.com/en/well_being/). Since we were able to control for all time-invariant individual-specific heterogeneity and we focussed on the same participants in each wave of our four-wave study, we could draw inferences about the evolution of perceived infectability, while controlling for some important confounders. Also, we carefully selected the four time points in this study. Our initial data collection (T1) took place in the middle of March 2020, at a time when the infection rates in Belgium were still at a relatively low level but exponentially increasing. Only a few days prior to this initial data collection, a country-wide lockdown had been announced. A second wave of this study (T2) was conducted in early April 2020, when infection and mortality numbers spiked for the first time (De Coninck *et al.*, 2020b, 2022). Belgium was under a strict lockdown, and its citizens had been informed that a first 'peak' of the pandemic was pending. A third wave of the study (T3) took place from late May 2020 to early June 2020, at a time when infection and mortality rates had declined, and a variety of government-imposed restrictive measures were being lifted. The fourth and final wave (T4) took place from late August 2020 to early September 2020, as infection rates spiked again for a second time and warning signs showed that a larger wave of infections was on the horizon (Figure 1).

PROCEDURE AND PARTICIPANTS

Data

The longitudinal data used in this article were collected during the COVID-19 pandemic in Flanders, Belgium. The aim was to investigate the dynamic interplay between perceived vulnerabilities regarding disease and news media consumption among adults aged 18–65 at key moments of the crisis. Data were collected in four periods in 2020: from March 17 to March 22 (T1; when the first restrictive measures went into effect; N = 1000), from April 6 to April 18 (T2; as hospital admissions and the death toll peaked; N = 870), from May 17 to June 5 (T3; as several measures were lifted or relaxed; N = 768) and from August 18 to August 31 (T4; as cases spiked for a second time; N = 558). The survey agency we collaborated with drew the initial sample out of its panel (150 000 individuals). Respondents were contacted by e-mail, and the survey was distributed via the polling agency's survey tool. Respondents were unable to skip questions, but some questions had a 'no answer'-option. Each question in the survey was presented on a different page, and there was no option to return to previous questions. All respondents with partial data were removed by the survey agency prior to delivering the fully anonymized dataset (De Coninck *et al.*, 2020b, 2022). All participants provided their written informed consent to participate in this study. The participants were able to end their participation at each time point, but were invited again after dropout. Half of all participants completed the survey at each time, while 6.7% of the participants participated again after one or more declines.

Perceived vulnerability to disease

We used a 15-item self-report instrument to assess perceived vulnerability to disease. Six of the items were reversely scored. Participants responded to each item on a 7-point scale with end categories labelled 'strongly disagree' and 'strongly agree'. This instrument was developed and validated by Duncan *et al.* (Duncan *et al.*, 2009) and has two subscales: one assesses beliefs about one's own susceptibility to infectious diseases (perceived infectability; eight items; Cronbach's α_{T1} = 0.85), e.g. 'If an illness is "going around", I will get it'. The other assesses emotional discomfort in contexts with an especially high potential for pathogen transmission (germ aversion; seven items; Cronbach's α_{T1} = 0.70), e.g. 'I do not like to write with a pencil someone else has obviously chewed on'.

Sociodemographic characteristics measured at T1 only

At T1 (also referred to as the baseline in the rest of this article), respondents were asked to indicate birth year (recoded to age), gender (1 = male, 2 = female), work status (full-time employed, part-time employed, temporarily/permanently disabled, unemployed, student, retired, houseman/wife), whether at least one of their parents (in law) aged over 60 years old were still alive (yes/no), marital status (1 = unmarried, 2 = legally or de facto cohabiting, 3 = married, 4 = legally or de facto separated, 5 = widowed) and whether they have children. In addition, their political orientation (1 = far left, 6 = far right), living environment (big city/small city/suburbs/countryside/village/other), educational attainment (primary education or lower/lower secondary education/higher secondary education/non-academic higher education/university degree) and province they lived in were also recorded.

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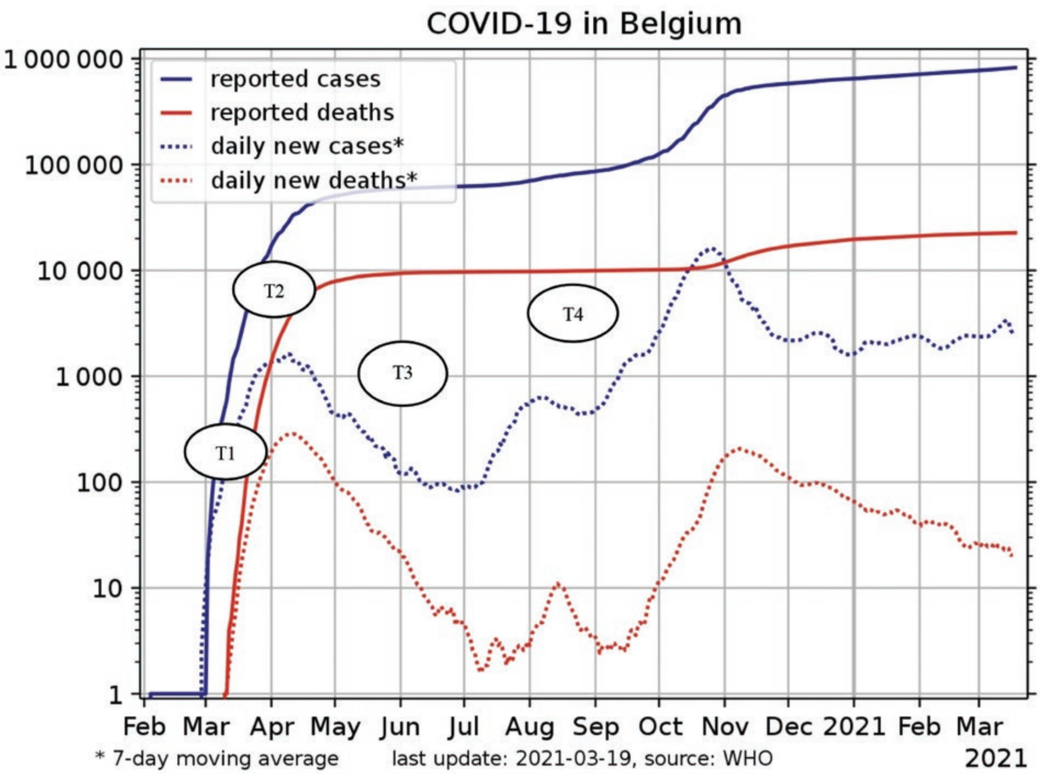

Fig. 1: Data collection dates and daily confirmed cases and deaths of COVID-19 in Belgium (in logarithms).

Sociodemographic characteristics measured at T1–T4

Several additional variables were included in each round: subjective monthly income (1 = very difficult to make ends meet to 6 = very easy to make ends meet), the ability to work from home (yes/no/NA), news media consumption (which is described in more detail in the next section) and whether they know/believe they currently have COVID-19 (yes/no). Due to four methodological considerations, only the value at baseline (T1) is included in the model. A first consideration is the substantial missingness in these variables after T1 (26.8%). Whereas the principle of ignorability under the assumption of missingness at random (MAR) is easy to apply for direct-likelihood inferences when dealing with missing response values (Rubin, 1976), a likelihood approach is more involved when there is also missing covariate information. A second methodological consideration is the challenge to correctly characterize the lag relationship between the time-dependent covariate and the outcome (Molenberghs *et al.*, 1998; Diggle, 2002). Thirdly, it must be decided whether the covariate is either endogenous or exogeneous. Endogeneity refers to the situation where the response predicts the covariate at later time points (Diggle, 2002). It is, e.g., not impossible that perceived vulnerability at a certain time point has an impact on the belief or knowledge of having COVID-19 at later time points. In addition, when endogenous covariates are included in a linear mixed model, the marginal interpretation of the coefficients does not hold anymore (Qian *et al.*, 2020). Lastly, it is possible that one or more time-dependent covariates are intermediate variables. An intermediate variable is a link in the causal pathway between a covariate and the response. When the analysis controls for these intermediate variables, the effect of the covariate mediated through these variables is lost (Diggle, 2002).

Consumption of (news) media

We asked about their exposure to eight Flemish news media sources by asking them to rate how often they followed COVID-19-related news on the following media sources in the week prior to the survey in each wave: (i) public television, (ii) public radio, (iii) quality newspapers, (iv) social media of public/quality news media, (v) commercial television, (vi) commercial radio, (vii) popular newspapers and (viii) social media of commercial/popular news media, (ix) internet, (x) face-to-face with family/friends/co-workers and (xi) social media contact with family/friends/co-workers. Examples of each media source were provided.

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Answer options ranged from 1 (never) to 5 (multiple times a day). Factor analysis with varimax rotation at T1 yielded a three-factor structure based on the scree plot and the >1 eigenvalue criterion (Kaiser, 1960): one factor with all four public/quality news media sources, one with all four commercial/tabloid news media sources, and one with internet, social media and face-to-face contacts (Table 1). All components showed reasonable reliability (Cronbach's α public/quality media sources = 0.574; Cronbach's α commercial/tabloid media sources = 0.601; Cronbach's α digital/face-to-face = 0.570). As a result, observations are divided into groups based on whether they scored higher or lower than the median of each factor. This new variable and corresponding interaction with time are added as fixed effects in the model.

FINDINGS

Exploratory analysis

To assess the overall mean profile of perceived infectability and germ aversion per wave, an exploratory analysis is presented (Figure 2). We observe that germ aversion was at its highest level at T2 (when infections in Belgium peaked for the first time) (dif $f_{T1-T2} = 0.232$, $p < 0.001$), and subsequently declined marginally (dif $f_{T2-T3} = -0.106$, $p < 0.001$; dif $f_{T3-T4} = -0.059$, $p = 0.061$). In terms of perceived infectability, we see that this was already at its highest level at T1, when the first Belgian lockdown measures went into effect, subsequently remained stable (dif $f_{T1-T2} = -0.026$, $p = 0.243$), and declined after T2 (dif $f_{T2-T3} = -0.173$, $p < 0.001$). Next, the average perceived infectability remained stable as infection rates remained low between T3 and T4 (dif $f_{T3-T4} = 0.005$, $p = 0.867$). To account for the longitudinal data structure, linear mixed models will be used later on.

A descriptive overview of the sample can be found in Appendix A. A full overview of the data for the four waves can be found in De Coninck *et al.* (De Coninck *et al.*, 2020b, 2022).

Inferential analysis

Two weighted mixed models were fitted to predict perceived infectability and germ aversion. Since these responses were repeatedly measured within respondents, a random effect was included at the individual level. Additional random effects were not considered as the observed variance and covariances remained fairly stable across the different time points. Because the sample did not fully mimic the population demographics based on age and gender, this was corrected via weights. More specifically, participants were weighted by the inverse selection probability based on gender and age to account for sampling bias (Heeringa *et al.*, 2010). The selection probability and sample size of each age category and gender are shown in Appendix B. A drawback for inverse probability weighting is when extreme weights are incorporated, large standard errors result (Vansteelandt *et al.*, 2010). Subjects with large weights are very highly influential and small deviations in their data can have large effects on the result, which causes the large standard errors.

The time point was included as a categorical variable in the models. The two initial models contained gender, work situation, educational level, age, media usage, perceived subjective income, working from home, political beliefs, province, living environment, presence of (grand)parent (in law) older than 60 and/or children, relationship status and (self-)diagnosis of COVID-19 at the baseline as fixed effects and the interactions between these covariates and wave. Although we included a number of indicators that we did not

Table 1: Factor loadings of the factor analysis after varimax rotation

	Commercial/tabloid	Public/quality	Digital/face-to-face
Commercial television	0.788	−0.054	0.076
Commercial radio	0.607	−0.159	0.229
Popular newspapers	0.563	0.338	−0.159
Social media channels of commercial/popular news media	0.673	0.198	0.301
Public television	0.143	0.697	−0.066
Public radio	−0.073	0.639	0.187
Quality newspapers	−0.06	0.628	0.0556
Social media channels of public/quality news media	0.189	0.553	0.311
Face-to-face contacts	−0.023	0.019	0.802
Internet	0.199	0.267	0.479
Social media of family, friends and colleagues	0.22	0.09	0.765

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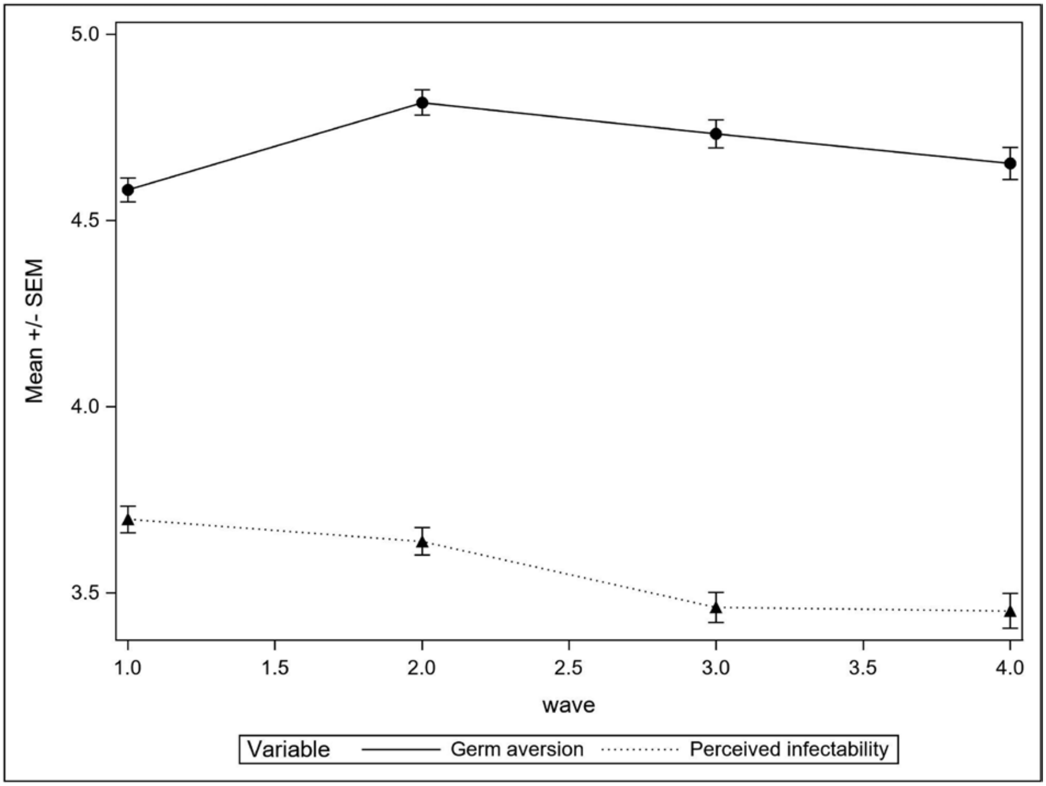

Fig. 2: Observed mean profile (with standard error bounds) for perceived infectability and germ aversion per wave.

discuss in the literature overview, we believe that—in order to develop a robust model to analyse within-person changes in perceived vulnerability to disease at the individual level—it was important to include all available indicators at the individual level.

After including these covariates, stepwise backward variable selection was performed as described in Kutner *et al.* (Kutner *et al.*, 2005). Based on the *F*-test, the predictor or interaction effect with the highest *p*-value was sequentially dropped until no effects with $p > 0.05$ remained. However, the principle of marginality was respected in each step, which encompasses that no main effect was dropped if its interaction effect with wave was still present in the model. In Appendix C, a sensitivity analysis is executed of the method of variable selection.

Perceived infectability

Perceived infectability, the first subscale of perceived vulnerability, was modelled using a linear mixed model. After backward variable selection, eight main effects and two interaction effects remained: the evolution of infectability depends on the age and the living environment.

The *F*-tests and corresponding *p*-values are shown in Table 2. The parameter estimates, standard errors, *t*-values and *p*-values can be found in Appendix D.

The expected perceived infectability of women was on average higher when compared with men. However, the evolution in expected perceived infectability across the four waves did not significantly differ between men and women, and this interaction effect was hence dropped from the model. The evolution of perceived infectability depended on the respondents' age ($F = 3.660$, $p = 0.012$). The age of a respondent interfered with the effect of T3 on the expected perceived infectability. On average, the expected perceived infectability of elderly respondents increased less than that of younger respondents at T3 ($\hat{\beta} = -0.006$, $p = 0.002$). Lastly, living environment significantly impacted the evolution of perceived infectability ($F = 3.660$, $p < 0.001$). At the last time point, respondents who lived in the rural areas ($\hat{\beta} = 0.381$, $p = 0.026$) or small cities ($\hat{\beta} = 0.210$, $p = 0.008$) had on average a steeper increase in expected perceived infectability compared with the persons who lived in a village.

Germ aversion

After variable selection, the second linear mixed model, for analysing germ aversion, contained twelve main effects and five interaction effects with time. The

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Table 2: *F*-values and *p*-values of the linear mixed models after variable selection for perceived infectability and germ aversion

Effect	Numerator df	Infectability		Germ aversion	
		F-value (*p*-value)	Standardized beta coefficient	*F*-value (*p*-value)	Standardized beta coefficient
Wave	3	0.632 (0.594)	—	2.111 (0.097)	—
Gender	1	14.527 (<0.001)	−3.812	42.757 (<0.001)	−5.896
Student	1	—	—	0.145 (0.704)	−0.247
Permanent disability	1	6.206 (0.013)	2.492	6.975 (0.008)	2.64
Living environment	5	13.311 (<0.001)	—	1.356 (0.238)	—
Biological grand (parents)	1	—	—	4.901 (0.027)	2.214
Grand (parents) in law	1	3.998 (0.046)	−1.999	—	—
Age	1	1.122 (0.290)	−0.119	27.265 (<0.001)	4.593
Children	1	—	—	4.726 (0.030)	2.173
COVID-19 at T1	1	30.509 (<0.001)	5.523	4.956 (0.026)	2.226
Working from home	2	—	—	0.058 (0.944)	—
Economic situation	1	35.778 (<0.001)	−5.982	21.667 (<0.001)	−4.655
Media usage	7	—	—	4.842 (<0.001)	—
Wave × Gender	3	—	—	3.911 (0.009)	—
Wave × Student	3	—	—	3.316 (0.020)	—
Wave × Living Environment	14	3.044 (<0.001)	—	5.376 (<0.0001)	—
Wave × Age	3	3.660 (0.012)	—	3.324 (0.019)	—
Wave × Working from home	6	—	—	3.447 (0.002)	—

F-tests and corresponding *p*-values can be found in Table 2. Appendix E displays the parameter estimates, degrees of freedom, *t*-values and *p*-values.

At baseline, women had on average a higher predicted germ aversion compared with men ($\hat{\beta} = -0.3458$, $p < 0.001$). The evolution of germ aversion was found to depend on the age of the respondent ($F = 3.324$, $p = 0.019$). Elderly respondents had on average a higher expected germ aversion at baseline than younger respondents ($\hat{\beta} = 0.014$, $p < 0.001$). In addition, at T2 elderly people had on average a higher increase in expected germ aversion ($\hat{\beta} = 0.005$, $p = 0.037$).

Media consumption had a significant effect on germ aversion at baseline ($F = 4.842$, $p < 0.001$). In particular, heavy consumers of only digital and face-to-face sources ($\hat{\beta} = -0.470$, $p < 0.001$), public news sources ($\hat{\beta} = -0.255$, $p = 0.013$) or both public and digital/face-to-face sources ($\hat{\beta} = -0.2925$, $p = 0.0049$) have on average a lower expected germ aversion compared with heavy consumers of both commercial and digital/face-to-face sources. Furthermore, respondents who were light consumers of all three sources (public, commercial, digital/face-to-face) had on average a lower expected germ aversion than the largest category (those who heavily consume both commercial and digital face/to face news) ($\hat{\beta} = -0.423$, $p < 0.001$).

Whether respondents were obliged or permitted to work from home at the beginning of the pandemic had a significant impact on the evolution of germ aversion. At T3, persons who were allowed to work from home ($\hat{\beta} = 0.2163$, $p = 0.002$) or for whom this did not apply (e.g. unemployed individuals) ($\hat{\beta} = 0.2890$, $p = 0.001$), had a steeper increase in expected germ aversion compared with respondents who were not able to work from home. Furthermore, respondents who could work from home ($\hat{\beta} = 0.2513$, $p = 0.001$) had at T4 on average a steeper increase in expected germ aversion compared with respondents who were not able to work from home.

Sensitivity analysis

The previous analyses are only valid under the assumption of MAR, i.e. under the assumption that the missingness can depend on the observed response and covariates, but not further on the actual value of the variable i.e. missing (Rubin, 1976). In order to assess how robust the conclusions are with respect to potential deviations from MAR, sensitivity analyses have been performed in which missing observations have been imputed under a missing not at random (MNAR) assumption, i.e. where in addition to observed data, also unobserved data have an impact on the missingness probability. Under such scenarios, variable selection is

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performed again. Missing values are imputed based on an upward shift relative to MAR, neighbouring cases (NCMV) and complete cases (CCMV). Under the latter two mechanisms, the conditional distribution of what is missing given what is observed, is borrowed from the pattern with one more measurement taken than in the pattern under study, on the one hand, or simply from the completers, on the other. A more detailed description of the methods and results can be found in Appendix F. In Tables F1 and F3–F5 the results of germ aversion are shown. Under all three MNAR imputations the significant effect of gender and media usage at baseline is still present. In addition, the interaction effect between student and gender and wave is present under each of the missing data assumptions. When it was assumed that respondents have a higher germ aversion than expected under MAR at times of dropout, the effect of age and the interaction effect of age and wave was no longer significant. Furthermore, the effect of working from home and the interaction effect between the latter and the timing in the pandemic was not significant anymore after imputation under CCMV. The results for the sensitivity analysis of infectability are shown in Tables F2 and F6–F8. The significant effect of gender and age at baseline was robust for the missing data assumptions. In contrast, the interaction effects with the timing are less stable. The interaction effect with age was only present in the model with imputations with an upward shift of infectability. The interaction effect with the living environment is not present in the final model with imputations based on NCMV.

DISCUSSION

In this study, we aimed to investigate the evolution of perceived vulnerability to disease throughout the first 6 months of COVID-19 among a sample of the adult population in Flanders, Belgium, using a longitudinal study design. Using panel data that were collected at four key points during the first 6 months of the pandemic, we were able to track respondents over time and control for individual random effects. We adopted an exploratory perspective: we considered a number of relevant sociodemographic characteristics to investigate if and how there were either baseline or interaction effects with time on perceived infectability and germ aversion, two subscales of perceived vulnerability to disease (Duncan *et al.*, 2009).

Findings indicate that at T1 (the baseline), we observe differences in perceived infectability and/or germ aversion based on gender, perceived financial vulnerability and media consumption. These findings were largely in line with previous studies: women reported greater perceived infectability and germ aversion than men [see (Galasso *et al.*, 2020)], and respondents whose income was enough to make ends meet reported lower perceived infectability/germ aversion than those whose income was not enough to make ends meet during the pandemic. These findings point to relevant gender and socioeconomic status differences in the fears regarding COVID-19. Finally, supporting assumptions made by Garfin *et al.* (Garfin *et al.*, 2020), we showed that respondents who were light commercial media consumers reported lower germ aversion than heavy commercial consumers. Given that commercial media often report a highly sensationalized and tabloidized coverage of events, Garfin *et al.* (Garfin *et al.*, 2020) expect that heavy consumers of these media types will experience greater fear of COVID-19. Looking back at the COVID-19 coverage of leading media outlets in Flanders, whether public or commercial broadcasters, a degree of unitary thinking could be observed, with health and healthcare issues taking precedence over other concerns, resulting in lower content differentiation in terms of actor and opinion diversity than in routine coverage (Walgrave and Kuypers, 2021). This may have caused people to look for alternative content in fringe news media and social media platforms as the crisis progressed.

Aside from these baseline effects at T1, we also found a number of interactions between sociodemographic characteristics and time. First, results showed that these interactions were mostly significant at T3 and T4, which were both time points when infections were relatively low in Belgium (Molenberghs *et al.*, 2020b). This indicates that at T2, when infections reached a first peak in early April of 2020, only one significant longitudinal difference was found with age. This is to be expected given that infections were at an all-time high at T2, with older individuals significantly more at risk of mortality than younger individuals if they contracted COVID-19. Beyond that, all longitudinal effects were found at T3 and T4. Although it is difficult to explain why this would be the case, perhaps the ‘crisis’ mode in which Belgium (and much of Europe) were in at this time hampered the differential growth of fear between sociodemographic groups. The country was in lockdown at T2, and deaths and infection rates were at a then all-time high. Given that many businesses were closed, the majority of the population remained locked down in their homes, and it is possible that in this highly threatening environment, fears were high among all layers and groups of the population. However, once the strict lockdown was removed and various rules were relaxed, these differences appeared. We observe a significant effect of age, living environment and working from home on the evolution of perceived infectability and/or germ aversion at T3 or T4. For age, we show that elderly respondents reported a lower decrease in infectability

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at T3 than younger respondents. This is consistent with findings by de Bruin (de Bruin, 2021), who found an absolute age difference in perceived infectability in a cross-sectional study. Although the elderly were clearly more at risk of mortality than younger age groups once they contracted COVID-19, it is possible that they were more eager to maintain lockdown measures (or maintained them for themselves, regardless of governmental regulations) and thus reduced their fear of contracting the disease while younger age categories ventured outside (e.g. for work) more quickly. We also found that people who lived in the countryside or in small cities reported a lower decline in infectability than people who lived in a village, likely due to the larger population (density) in small cities than in more rural villages. Finally, being able to work from home stimulated a larger increase in germ aversion than those who were unable to work from home: those who were forced to leave their homes clearly reported lower fears than those who were able to remain at home for a longer period of time. A potential explanation for this may be that people who were unable to work from home were used to leaving the house and interacting with others while those who worked from home were not, which may stimulate the greater increase in germ aversion that was found among this latter group.

A limitation of the study is that the sample was not completely representative in terms of age and gender. To take this into account in the analysis, weights were incorporated. Overall, though, these findings may be used by policy makers and media professionals to obtain more information about how fears regarding the possibility of getting sick during a pandemic do not only evolve over time, but also how this evolution depends on a number of individual characteristics. By targeting these specific groups in campaigns or making further efforts to inform them of the various protective behaviours they can adhere to in order to reduce the risk of infection, fears of infection may be reduced.

Supplementary Material

Supplementary material is available at *Health Promotion International* online.

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Conflict of Interest

None declared.

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