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Maastricht University

Faculty of Sciences
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Master of Statistics and Data Science

Master's thesis

Expected performance of testing and isolation strategies in Belgium to manage COVID-19 in Winter 2022-2023

Anne Marie Shudzeka Sevidzem

Thesis presented in fulfillment of the requirements for the degree of Master of Statistics and Data Science, specialization Biostatistics

SUPERVISOR :

dr. Lisa HERMANS

MENTOR :

De heer James WAMBUA

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2023

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Sevidzem Anne Marie Shudzeka

16 June 2023

Contents

List of Figures

List of Tables

Abstract

Background Continuous adherence to testing and isolation (TI) behaviours remains pivotal in the non pharmaceutical management of the COVID-19 disease. Compliance to these behaviours is even more crucial during peak seasons with a potential surge of Omicron subvariants. With an established baseline of expected testing and isolation behaviour of participants in Belgium during the summer, and with subsequent targeted interventions focusing on testing and isolation, it was of essence to assess the expected performance of these behaviours during the winter, to evaluate the effectiveness of implemented management strategies. Understanding the association between TI behaviours and perceptions on COVID-19 can further inform future management strategies.

Objectives The main objective of this study was to assess the expected performance of testing and isolation behaviours under (a)symptomatic and (un)vaccinated conditions in Belgium, during the fall and winter seasons of 2022-2023. The secondary objective was to investigate the association between TI behaviours and perceptions on COVID-19.

Methodology Logistic regression models were employed to obtain adjusted odds ratios of expected testing and isolation by vaccination status. Contingency tables were used to compute expected adjusted odds ratios of testing and isolation by symptomatic status and their 95% Wald confidence intervals were calculated using Woolf's formula. Generalised additive models for location, scale and shape (GAMLSS) with a non linear term for the time variable were implemented to obtain adjusted odds ratios of winter testing by vaccination and symptomatic status. Likewise, GAMLSS models were also implemented to analyse the association between testing behaviour and perceptions on COVID-19.

Results Winter testing behaviour was in general more extreme than was expected. Symptomatic status was significantly associated with winter testing contrary to expectations, with symptomatic individuals having significantly higher odds of testing than asymptomatic individuals. Vaccination status was insignificantly associated with testing behaviour both at baseline and during the winter. Participants with higher perceived susceptibility who take medication had significantly lower odds of testing than those with a low perception who are not taking medication. The highly educated with higher perceptions on long term impact had significantly lower odds of testing than the less educated with a low perception, while those with higher perceptions on the benefit of vaccination had significantly higher odds of testing than those with a low perception. Perceptions on severity and benefit to the vulnerable had inconclusive findings on their association with testing behaviour and require further investigation.

Conclusions The assessment of testing behaviour during the winter revealed more extreme testing performance among the symptomatic than was expected, indicative of successful pre-winter COVID-19 management interventions focused on testing and isolation. The results highlight a potential pandemic fatigue in testing among individuals with co-morbidities who have higher perceptions on susceptibility. There is a potential barrier to testing among the highly educated with higher perceptions on the long term impact of COVID-19. Meanwhile, a low perception on the benefit of vaccination is negatively associated with testing behaviour. Future campaigns are needed to encourage more testing among the highly susceptible with co-morbities and among the highly educated who are highly concerned about the long term impact of COVID-19. There is also a need to modify low perceptions on benefit of vaccination, to improve testing rates in the fight against the COVID-19 pandemic.

Key words: Human behaviour and perception, syndromic surveillance, COVID-19, testing and isolation protocols

1 Introduction

The COVID-19 pandemic that has lasted since 2019 has been a huge cause of morbidity, mortality and socio-economic burden to many countries world-wide[1,12,13,14,15]. As a result, its effective management has been a major concern of the World Health Organisation as well as ministries of health and public health agencies worldwide[16]. Being of a highly infectious nature with transmissions occurring via the respiratory route and through contact mechanisms[12,13], human behaviour plays a paramount role in the control and containment of the spread of the disease[1]. Over the past three years, many testing and isolation protocols were and are still being recommended to prevent an infectious person from transmitting the virus to those around them. To this end, early detection through testing and subsequent isolation of infected persons are crucial for the effective management of COVID-19. Continuous monitoring of the pandemic situation with plans to contain potential spikes remains of paramount importance in the management scheme.

In order to counter a potential surge of Omicron subvariants during the winter of 2022-2023, there was a need for continuous testing and isolation, and focus was placed on strategies to ensure that such behaviours continued to be upheld. This was especially important as widespread pandemic fatigue and limited compliance could undermine mitigation efforts[10]. In order to establish a baseline for management interventions, information was collected from survey participants in the summer of 2022 about their expected testing and isolation behaviour during the fall and winter seasons of 2022-2023, and about their perceptions on COVID-19. With continuous interventions thereafter, focusing on enforcing testing and isolation habits, it was of essence to assess the expected performance during the fall-winter of 2022-2023.

The main aim of this study is to assess the expected performance of testing and isolation behaviour in Belgium, during the fall and winter seasons of 2022-2023. These are seasons with a high potential for the surge of subvariants, and non pharmaceutical management strategies like testing and isolation are crucial in managing the spread of the disease. Conventional surveillance tools of symptoms and testing may give a distorted picture as they rely on patients who seek medical care[11]. This is because during a pandemic, people may tend to change their health seeking behaviour such that those with mild symptoms, may be more health seeking than usual due to heightened awareness, or on the contrary may be less bothered. As a result, some individuals who get infected with mild symptoms may not seek medical care making the tracking of symptoms and testing behaviour difficult. Therefore, in this study, the monitoring of COVID-19 symptoms was done via a web-based participatory syndromic surveillance platform called Infectieradar.be[11]. Infectieradar.be is a part of Influenzanet which constitutes a partnership between various European universities and government agencies, of which Hasselt University is a part. Its main purpose is to map and monitor symptoms of respiratory infections including influenza-like infections (ILI) and COVID-19 in various European countries, with the aim of using the data for scientific research[3]. In effect, Infectieradar.be monitors respiratory infection and its spread by looking at the symptom burden in real time, and as such was utilized to monitor symptoms and testing behaviour during the fall and winter seasons. In this study, the assessment of expected testing and isolation was done under vaccinated and unvaccinated, as well as symptomatic and asymptomatic conditions, to gain insight into how individuals' testing and isolation behaviour is driven under these conditions. The study also seeks to understand how the testing and isolation behaviour of individuals is associated with their perceptions on COVID-19.

Studies have been conducted to validate the infectieradar.be monitoring tool[2], and to investigate the influence of perceptions on other COVID-19 management behaviours like close contact frequency[1]. The studies respectively validated the use of infectieradar.be as a reliable monitoring tool for ILI and COVID-19 infections, and found significant associations between perceptions and close contact frequency. To add to the wealth of knowledge in the fight against the COVID-19 pandemic, this study also investigates the influence of perceptions on other management behaviours of testing and isolation. Findings from this study can be used to tailor public health strategies by targeting perceptions that are negatively associated with testing and isolation. For simplicity purposes, the use of winter in this paper refers to the fall-winter season.

2 Problem statement and research objectives

2.1 Problem statement

Given that the COVID-19 pandemic has lasted for a long time with constantly evolving complexities, there is a need for continuous adherence to testing and isolation (TI) protocols in order to consistently keep the disease under control. However, there is a tendency that individuals are getting fatigued and gradually non compliant to TI protocols that have been put in place by the ministry of health and public health agencies. With the emergence of subvariants of the SARS-CoV-2 virus which can potentially surge during the fall and winter months, it was crucial to implement campaign strategies targeting TI behaviour during these months in order to contain a potential COVID-19 wave with re-surging subvariants. To this aim, baseline testing habits of participants were obtained in the summer stating their expected TI behaviours during the fall and winter months. Following intervention strategies thereafter that focused on TI behaviours, it was of high importance to assess the expected performance of testing and isolation during the winter months in order to evaluate the effectiveness of implemented management interventions. It was of essence to do the assessment under different conditions i.e. vaccinated and unvaccinated as well as symptomatic and asymptomatic conditions in order to gain more insight into the factors driving testing and isolation behaviours. While the primary aim focused on assessing expected TI behaviour during potential peak seasons of the COVID-19 pandemic, a secondary aim was to investigate the association between TI behaviour and perceptions on COVID-19. This can identify perceptions that are negatively influencing TI behaviour requiring modification as well as misaligned associations between perception and TI behaviour requiring intervention.

2.2 Primary objective

To assess the expected performance of TI protocols in Belgium during winter 2022-2023 under different conditions i.e., vaccinated/unvaccinated and symptomatic/asymptomatic.

2.3 Secondary objective

To analyse the association between TI protocols and perceptions on COVID-19.

3 Description of the data set

A nationwide survey was launched in Belgium via infectieradar.be platform since March 2021 in order to monitor respiratory infections including ILI and COVID-19. Participants of age 18 years or older with internet access were and are still being invited to voluntarily sign up into this platform with an email address and a password. Upon signing up, they complete an initial registration form with baseline information about their work, age, existing diseases and health condition. Subsequently, they receive an email every week with a link to a symptoms questionnaire. In the questionnaire they are asked if they had any symptom(s) in the previous week, and if so which symptoms: a runny nose, coughing, sneezing, a high temperature etc. The questionnaire also inquires if the individual tested in the previous week. Survey data for minor participants is submitted by their parents or legal guardians through their main accounts. This is an on-going surveillance and information is constantly being updated on a weekly basis in order to monitor the infectious disease symptom burden in real time and also testing behaviour.

Four data sets obtained through this platform were used to address the objectives in this study. The data sets contained information about baseline characteristics, vaccination status, testing habits and perceptions obtained during the summer of 2022, as well as weekly observations on symptoms and testing behaviour obtained during the fall and winter seasons of 2022-2023. The data sets were merged so as to include subjects who participated in the summer survey and later in the winter survey with the incorporation of their baseline and vaccination information. The final dataset thus included all pertinent variables combined from the four data sources. It is a longitudinal data set with weekly observations on symptoms and testing over a period of 27 weeks, from September 2022 to February 2023. It consisted of 756 participants and 28793 observations in total. A cross sectional data set was

also obtained which excludes the weekly observations in the winter. The main variables included in the analyses were expected testing, expected isolation, winter testing, vaccination status, symptomatic status, sex, age, medication status, main activity, mode of transport, education level, week (time), province, expected (a)symptomatic testing, expected (a)symptomatic isolation and the five perception variables. The perception variables pertain to severity, susceptibility, benefit to the vulnerable, long term impact and benefit of vaccination. A more elaborate explanation of the perception variables is presented on Table 1. A description of all variables and their categories as used in the analyses is presented on Table 2. Details on pre-processing of raw data and coding of variables are presented on Appendix Table 7.

Table 1: Construction of perception variables and their categories

Questionnaire item	**Variable**
COVID-19 would be a serious illness for me	Perceived severity
I'm likely to catch COVID-19 (again)	Perceived susceptibility
I'm worried that I might spread COVID-19 to someone who is vulnerable	Perceived benefit to the vulnerable
I'm concerned about the possible long-term impacts of COVID-19 for myself	Perceived long term impact
It is important that people in my community are vaccinated	Perceived benefit of vaccination

Responses and coding for all perception variables

Responses	**Category and coding**
'Strongly agree' and 'Tend to agree'	High perception (agree) = 2
'Neither agree nor disagree' and 'I don't know'	Moderate perception (neutral) = 1
'Strongly disagree' and 'Tend to disagree'	Low perception (disagree) = 0

4 Methodology

In this section, methods for data exploration and statistical analyses are discussed. All tests and p-values were based on a 5% significance level, and the corresponding 95% confidence intervals were reported. Potential confounders for each model were chosen based on causal thinking and an extensive literature review of a potential association with both the target covariate and the outcome variable. Model building consisted of choosing the best variance structure for the data and the best mean structure for each model. Potential confounders were added to the models and retained whether significant or not. All statistical analyses were done using `R` software version 4.1.1. The `lme4` package was used for the logistic mixed models which were later found to be limited and the `gamlss` package was used for the generalized additive models for location scale and shape.

4.1 Methods for data exploration and missingness

A baseline summary statistics table was constructed presenting proportions for each variable by vaccination status. The mean and range of the age variable were also reported. Bar charts were plotted with overall participant counts in the different perception categories for all perception variables. Bar charts were also plotted displaying the proportion of participants in each perception category by gender and age group for all perception variables. In order to explore testing behaviour across the 27 weeks of study, plots were presented showing the weekly proportions of testing and non-testing by symptomatic

and vaccination status. A histogram was also plotted showing the distribution of the total number of tests per participant.

To explore missing data, plots were generated displaying missing data proportion summaries for baseline and perception variables, and missing data patterns. The proportion of missing records (weeks with no entry) on symptoms and testing was also computed and reported.

Table 2: Description of variables used in the analyses. perception* applies to each of the 5 perception variables.

Variable	Description	Levels
test	Binary outcome variable for expected testing	1 = Yes, 0 = No
isolation	Binary outcome variable for expected isolation	1 = Yes, 0 = No
cov_test	Binary outcome variable for winter testing	1 = Yes, 0 = No
vacc	Factor variable for vaccination status	vacc1=vaccinated vacc0 = unvaccinated
symptom	Factor variable for symptomatic status during winter	symptom1= had symptoms symptom0 = had no symptoms
sex	Factor variable for gender	sex1=male sex0 = female
age_grp	Factor variable for age group (years)	age_grp1=1-29 (young) age_grp2 = 30-59 (middle aged) age_grp3 = 60-89 (old)
med	Factor variable for medication status	med1=on medication med0 = not on medication
outdoor	Factor variable for main activity	outdoor1=main activity outdoor outdoor0=main activity indoor
Educ_high	Factor variable for education level	Educ_high1=high Educ_high0=low to moderate
Public_transp	Factor variable for mode of transport	Public_transp1=public transport Public_transp0=private transport
province	Factor variable for province	11 levels for each of the provinces
week	integer variable for week	ranges from 0-26 weeks
perception*	Factor variable for perception	high perception (agree) =2 moderate perception (neutral) = 1 low perception (disagree) = 0
symp_test	Factor variable for expected symptomatic testing	1 = Yes, 0 = No
asymp_test	Factor variable for expected asymptomatic testing	1 = Yes, 0 = No
symp_iso	Factor variable for expected symptomatic isolation	1 = Yes, 0 = No
asymp_iso	Factor variable for expected asymptomatic isolation	1 = Yes, 0 = No

4.2 Statistical analyses of expected testing and isolation behaviour

The expected odds ratios (OR) of testing and isolation by vaccination and symptomatic status were analysed from the cross sectional data. The expected odds ratios for testing and isolation by vaccination status were obtained by fitting logistic regression models which adjusted for potential confounders age, sex, medication and education status. Logistic regression models were suitable due to the binary nature of the outcome variables of testing and isolation, and the independence of the observations. Model building consisted of checking for significant interactions between vaccination status and potential confounders. Significant interactions and main effects of all potential confounders were retained in the final models. The respective final models for testing and isolation by vaccination status are presented

on Equations (1) and (2). They respectively model the logits of the probability of testing or isolation for the i^{th} participant π_i as a linear function of the vector of covariate values of the i^{th} subject X_i, for i = 1,2,...,756.

$$
\begin{aligned}
&test_i \sim Bernoulli(\pi_i),\\
&\text{logit}(\pi_i) = \beta_0 + \beta_1 vacc1_i + \beta_2 sex1_i + \beta_3 age\_grp2_i + \beta_4 age\_grp3_i + \beta_5 Educ\_high1_i + \beta_6 med1_i, \quad (1)\\
&\text{logit}(\pi_i) = \text{logit}(P(test_i = 1|\boldsymbol{X_i})
\end{aligned}
$$

$$
\begin{aligned}
&isolation_i \sim Bernoulli(\pi_i),\\
&\text{logit}(\pi_i) = \beta_0 + \beta_1 vacc1_i + \beta_2 sex1_i + \beta_3 age\_grp2_i + \beta_4 age\_grp3_i + \beta_5 Educ\_high1_i + \beta_6 med1_i, \quad (2)\\
&\text{logit}(\pi_i) = \text{logit}(P(isolation_i = 1|\boldsymbol{X_i})
\end{aligned}
$$

Model diagnostics for both logistic models was done by examining plots of standardized deviance residuals and influence plots of studentized residuals as well as Cook's D values.

The variables for expected symptomatic and asymptomatic testing as well as symptomatic and asymptomatic isolation were each used to construct contingency tables stratified by potential confounder variables age group, sex and outdoor (main activity). Odds ratios for expected testing and isolation under symptomatic and asymptomatic conditions were then computed as a ratio of the cross product of cell frequencies[8]. Respective interaction odds ratios for symptomatic status and each potential confounder were then computed as presented on Equation (3)[21]. The respective 95% Wald confidence intervals were computed using Woolf's formula[8], which calculates confidence intervals for the log odds ratios and then exponentiate the limits. The standard errors of the log odds ratios were calculated as the square root of the sum of the reciprocals of all cell frequencies used to compute the odds ratio[8]. The resulting odds ratios and confidence intervals that were computed are presented on Table 4.

$$Interaction(OR) = \frac{OR(symptomatic)}{OR(asymptomatic)} \quad (3)$$

4.3 Statistical analyses of actual testing during winter

In order to analyse testing during the winter under (un)vaccinated and (a)symptomatic conditions, the generalized linear mixed model framework was initially employed due to the discrete nature of the outcome and the repeated observations over time. Specifically, since the outcome was of a binary nature, the logistic mixed effects models were utilized with the inclusion of random subject-specific intercepts, to account for the correlation induced by repeated observations within a participant. The addition of random slopes did not significantly improve the fit of the random intercept models based on AIC, BIC, log likelihood and Deviance criteria. Also an inclusion of random intercepts for province to verify if responses within a province are correlated, resulted in over-fitting due to a low frequency of participation in some provinces. However the logistic mixed models were found to unexpectedly have **significant** linear time effects. Looking at the exploratory plots presented on Figure 4, one would not expect linear time trends to be significant. This presented a need to validate the models. However, plots of Pearson residuals versus fitted responses on the logit scale from logistic mixed models do not provide information about validity of assumptions or fit of the model. Hence, in the absence of a meaningful method to diagnose the logistic mixed models, Generalised Additive Models for Location Scale and Shape (GAMLSS) were considered as a more appropriate modelling approach for the longitudinal data.

In order to demonstrate the limitation of the logistic mixed models for this study, and validate the importance of the GAMLSS models, the AIC fits for the respective models were compared. To this end, using the formulation of the logistic mixed models, GAMLSS models were fitted with and without a non linear term for time. Table 3 presents the AIC fits for the logistic mixed models, and for the GAMLSS models with and without a non linear term for time. The GAMLSS models were found to have a much better fit compared to the logistic mixed models, and specifically the GAMLSS model with non linear time had the best fit. This validated that GAMLSS models are more efficient for the

Table 3: Comparing AIC fits for logistic mixed models and GAMLSS models with linear and non linear time

	Logistic mixed	GAMLSS(linear time)	GAMLSS(non linear time)
Vaccination model	5337.9	4837.288	4770.360
Symptom model	3857.8	3438.024	3421.319

analysis and that time is not linearly related to the link function. This implies a potential violation of the linearity assumption in the logistic mixed models.

GAMLSS models which are used for flexible regression modelling, are a suitable alternative modelling approach, when linearity and/or parametric assumptions of generalized linear (mixed) models are potentially violated. A GAMLSS model extension which includes a non linear term for the time variable was therefore adopted for the analysis. This results in a parametric GAMLSS model with a combination of linear and non linear terms in the systematic component. In this formulation, the logit of the mean of the response distribution is modelled as a non linear function of the time variable, but as a linear function of other covariates as well as the random intercepts. In this study, the response outcomes y=1,2,...,n=756 are assumed to follow a binomial distribution with parameters n and μ with the mean of the binomial distribution being nμ and the variance nμ (1-μ) [4]. Therefore, each response outcome is assumed to follow a Bernoulli distribution with parameter μ, which is modelled using the logit link.

Model building was re-visited under the GAMLSS framework to obtain the most appropriate mean structure for each model, while retaining the previously validated random effects structure (random intercepts). To this end, interactions between non linear time and all variables was verified. Significant non linear time interactions with potential confounders and all other confounder main effects were further checked for significant interactions with the target covariate. This led to some three way interactions, which were however found insignificant and were dropped from the models. The final models thus included all significant non linear time interactions as well as significant interactions between the target covariate and confounders. The model for testing by vaccination status adjusted for age, sex, education and medication status as potential confounders, while the model for testing by symptomatic status adjusted for age, sex, mode of transport and main activity. Specific findings for each model building are presented in the following paragraphs.

In model building for testing by vaccination status, there were significant non linear time interactions with sex and age group, but no significant interactions between vaccination status and confounders. The final model thus included the significant non linear time interactions with sex and age group, and the main effects of vaccination, medication and education status (Equation (4)).

In model building for testing by symptomatic status, there were no significant interactions between covariates and non linear time, but there were significant symptomatic status interactions with sex, age group and main activity (outdoor). The final model included these significant interactions and main effects of time and transportation (Public_transp) (Equation (5)).

$$
\begin{aligned}
&cov\_test_{ij}|b_i \sim Bernoulli(\mu_{ij}),\\
&\text{logit}(\mu_{ij}) = \beta_0 + b_i + h_{ij}(\beta_1 week_{ij}) + \beta_2 vacc1_i + \beta_3 sex1_i + \beta_4 age\_grp2_i + \beta_5 age\_grp3_i + \beta_6 Educ\_high1_i +\\
&\beta_7 med1_i + \beta_8 sex1_i * h_{ij}(week_{ij}) + \beta_9 age\_grp2_i * h_{ij}(week_{ij}) + \beta_{10} age\_grp3_i * h_{ij}(week_{ij}),\\
&\text{logit}(\mu_{ij}) = \text{logit}(P(cov\_test_{ij} = 1|b_i, h_{ij}(week_{ij}), \boldsymbol{X_i})\\
&\boldsymbol{b_i} \sim N(\mathbf{0}, D)\\
&h_{ij} = \textit{non linear function of week j for subject i}
\end{aligned}
\tag{4}
$$

$$
\begin{aligned}
&cov\_test_{ij}|b_i \sim Bernoulli(\mu_{ij}),\\
&\text{logit}(\mu_{ij}) = \beta_0 + b_i + h_{ij}(\beta_1 week_{ij}) + \beta_2 symptom1_i + \beta_3 sex1_i + \beta_4 age\_grp2_i + \beta_5 age\_grp3_i + \beta_6 outdoor1_i +\\
&\beta_7 Public\_transp1_i + \beta_8 symptom1_i * sex1_i + \beta_9 symptom1_i * age\_grp2_i +\\
&\beta_{10} symptom1_i * age\_grp3_i + \beta_{11} symptom1_i * outdoor1_i,\\
&\text{logit}(\mu_{ij}) = \text{logit}(P(cov\_test_{ij} = 1|b_i, h_{ij}(week_{ij}), \boldsymbol{X_i})\\
&\boldsymbol{b_i} \sim N(\mathbf{0}, D)\\
&h_{ij} = \textit{non linear function of week j for subject i}
\end{aligned}
\tag{5}
$$

4.4 Statistical analyses of the association between testing and perceptions

Analyses on the association between testing and perceptions were also done using the longitudinal data set and based on the GAMLSS framework. Model building proceeded in a similar manner as described in section 4.3.2. Potential confounders considered for the perception models were sex, age group, education and medication status. Model building findings for each perception variable are presented in the following paragraphs.

In the model building for perceived severity, there were significant non linear time interactions with sex and age group, as well as significant perceived severity interactions with medication and education status. The final model thus included non linear time interactions with sex and age group, as well as perceived severity interactions with medication and education status. This formulation retained all confounders naturally through the significant interactions.

For perceived susceptibility model building, there were significant non linear time interactions with perceived susceptibility, sex and age group. Further building found a significant interaction between perceived susceptibility and medication status. The final model included non linear time interactions with perceived susceptibility, sex and age group, interaction between perceived susceptibility and medication status and the main effect of education status. However, upon fitting the final model, the interaction between perceived susceptibility and non linear time became insignificant, and was removed from the final model.

The model building for perceived benefit to the vulnerable revealed significant non linear time interactions with sex and age group. Further model building also found a significant interaction between perceived benefit to the vulnerable and medication status. The final model included the significant non linear time interactions with sex and age group as well as the significant interaction between perceived benefit to the vulnerable and medication status and the main effect of education status.

For perceived long term impact, there were also significant non linear time interactions with sex and age group. Further interaction check between perceived long term impact and all terms found a significant interaction between perceived long term impact and education status. The final model included all significant interactions and the main effect of medication status.

Model building for the association between testing and perceived benefit of vaccination revealed significant non linear time interactions with sex and age group. Additional interaction check between target covariate and all terms found no additional significant interactions. The final model thus included non linear time interactions with sex and age group, and the main effects of perceived benefit of vaccination, medication and education status.

The non linear term for time was implemented by use of penalised beta functions. They estimate smoothing parameters using different local methods, and are therefore more efficient and faster than the original penalised smoothing functions[5]. Model diagnostics involved inspecting plots of randomised quantile residuals i.e., residuals versus fitted values, residuals versus index, density and normal Q-Q plots[6].

4.5 Sensitivity analysis

Two types of sensitivity analyses were done to validate the importance of the longitudinal study, and to check the robustness of the results to the inclusion of subjects with little participation. To validate the importance of the longitudinal study, a model was fitted with participants who tested at least

3 times. Of the 756 participants in the study, 349 tested during the 27 week study period. Of the 349 participants who tested, 279 tested once or twice. Specifically, 182 participants tested once and 97 tested twice. The subset of participants who tested at least thrice translated to a total of 11,280 observations of the 28793 observations in the complete dataset.

The second sensitivity model included only subjects who participated at least 3 times i.e., who completed at least 3 weekly questionnaires during the study period, whether they tested or not during these occasions. In this approach, it was found that 57 subjects participated once or twice, while 699 participated at least 3 times. The sensitivity model utilized 28725 of the total 28793 observations in the complete dataset.

5 Results

5.1 Data exploration and missingness

The baseline summary characteristics of the participants under study are presented on Appendix Table 8. The number of unvaccinated participants was very small (1.46%) compared to the vaccinated participants. A majority of the participants were in the middle and old age groups, with only a small proportion in the young age group (2.8%). Apart from the 12 participants below 5 years old who largely constituted the 13 participants with missing vaccination data, all other participants in the young age group were vaccinated. Most of the participants utilized non public transport modes, and only a small proportion who were all vaccinated, utilized public transport (4.8%). A large majority of the participants were resided in Antwerpen, Limburg, Oost-Vlaanderen, Vlaams-Brabant and West-Vlanderen, with only a few (less than 2%) residing in each of the other provinces. The unvaccinated participants were all resident in Antwerpen, Limburg, Oost-Vlanderen and Vlaams-Brabant, with the rest of the provinces having no unvaccinated participants. The age of the participants in the survey ranged from 1 to 85 years old, with an average age of 63.8 years.

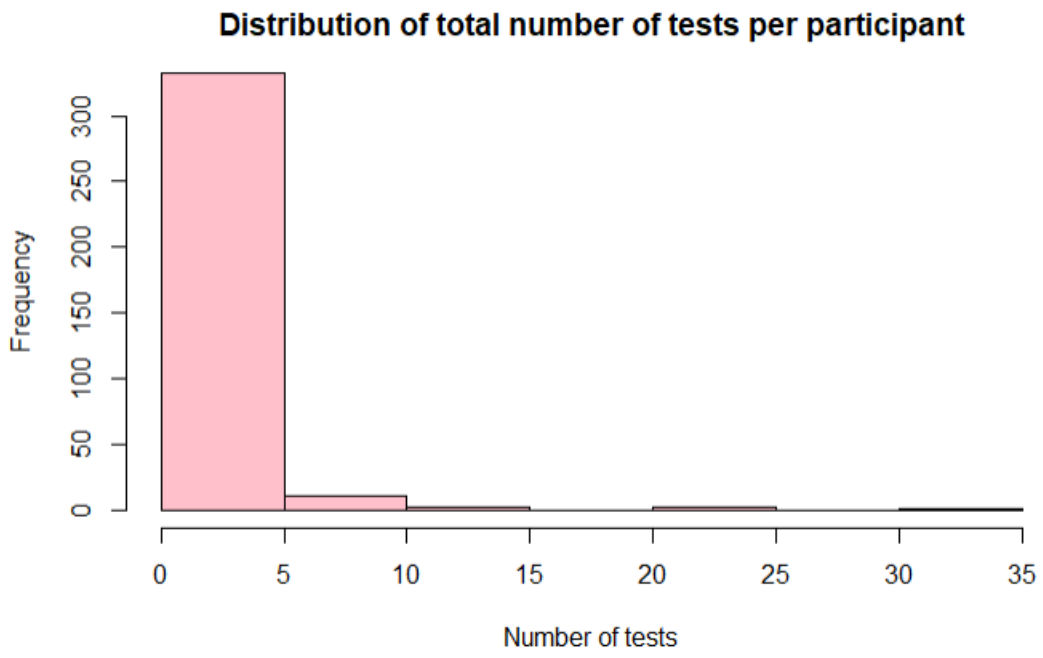


Figure 1: Histogram showing the distribution of the total number of tests per participant

A histogram showing the distribution of total number of tests per participant is presented on Figure 1. It shows that a majority of the participants tested 1 to 5 times, and a substantial proportion tested up 10 times, with few extending to 15 times. There were 3 outlying participants, including 2 who tested 25 times and 1 who tested 33 times.

Bar charts displaying participant counts in the different perception categories, for each perception

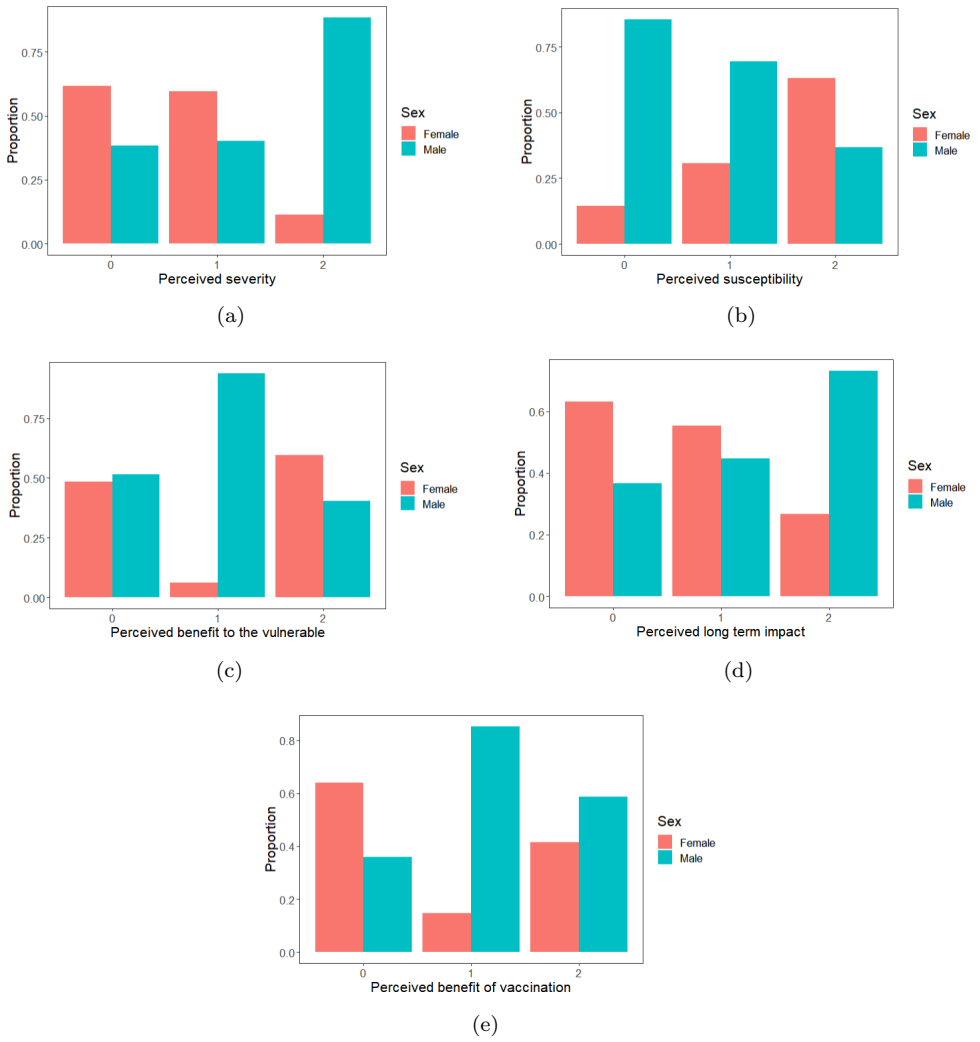


Figure 2: Proportion of participants in the different perception categories by sex for all perception variables.

variable are presented on Figure 9 in the Appendix. For all perception variables except perceived susceptibility, a majority of participants reported a high perception (agreed). Meanwhile, a majority of the participants had a neutral perception about susceptibility. Very few participants had a low perception on benefit to the vulnerable and on the benefit of vaccination.

Bar charts showing the proportion of participants at each perception category by gender, for all perception variables are also presented on Figure 2. A much higher proportion of males than females have a high perceived severity, and conversely a much lower proportion than females have a high perceived susceptibility. More males had a high perception about the long term impact of COVID-19, while more females had a low perception. A very large majority of males were neutral about benefit to the vulnerable, with more females having a high perception. A large majority of males had a moderate to high perception about the benefit of vaccination, with more females having a low perception.

Perception summaries by age group are also displayed on Figure 3. A majority of the old participants had a high perception about severity, and conversely very few young participants had a high perception. Most old participants had low to moderate perception about susceptibility, with more middle aged having a high perception, and very few young participants having a low perception. For all perception categories of benefit to the vulnerable, the old were a majority followed by the middle age, with most of the old being neutral. For perceived long term impact, majority of the middle-aged had a low to moderate perception, while a majority of the old had a moderate to high perception. Most of the middle-aged had a low perception on the benefit of vaccination, while the old mostly had

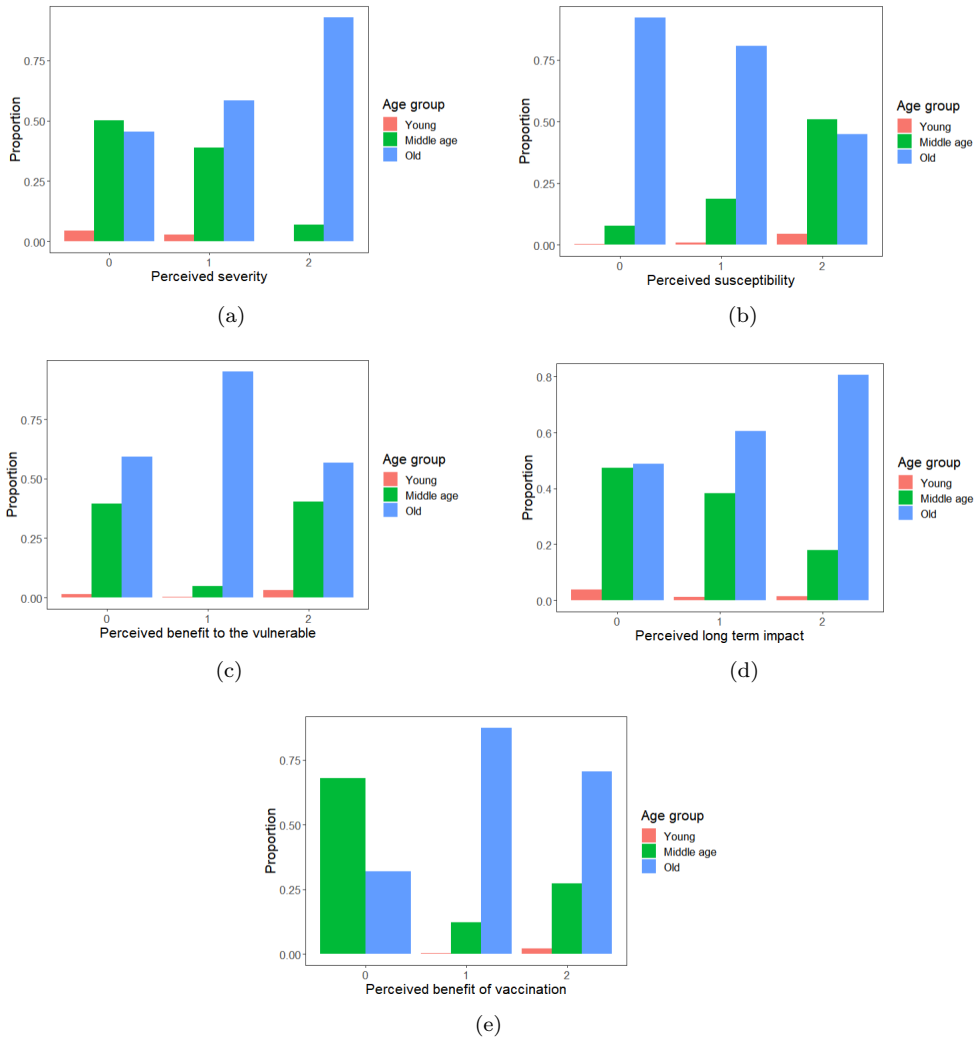
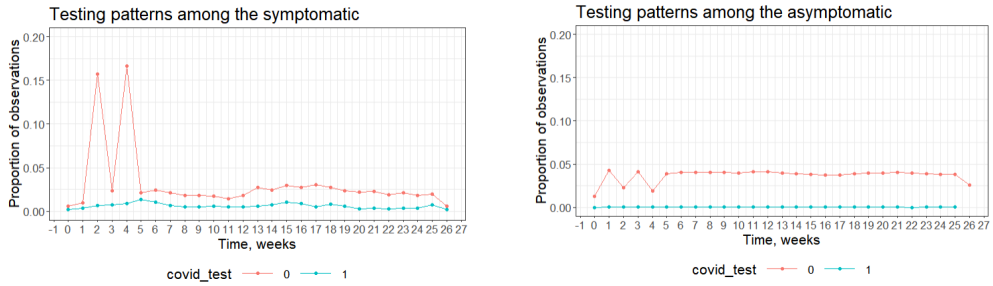


Figure 3: Proportion of participants in the different perception categories by age group for all perception variables.

a moderate or high perception.

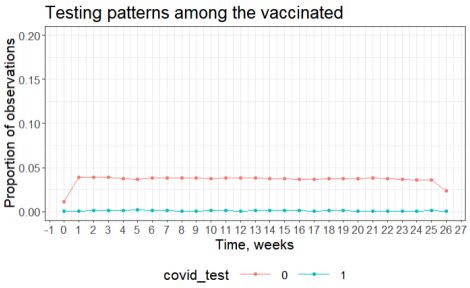
Figure 4 presents the evolution of winter testing proportions by symptomatic and vaccination status, across the 27 week study period. Testing proportions were fairly constant across the 27 weeks for the vaccinated and asymptomatic, with more fluctuations noticed for the symptomatic and unvaccinated. Testing proportions were smaller than non testing proportions for all conditions. The unvaccinated apparently stopped testing around the middle of the study in week 14, which corresponds to the week of December 5-11, 2022. This is probably due to the few participants in the unvaccinated category.

A thorough exploration of missingness in baseline and perception variables is summarised on Figures 5 and 6 respectively. For the baseline variables, there was missing data only for age (0.13%) and vaccination (1.69%). Two missing data patterns were noted for baseline variables, with one pattern having missing data only for vaccination, and the other for both age and vaccination. The overall proportion of missingness for baseline variables was 0.2%. With regards to perception variables, there was missing data only for perceived severity (4.07%). The overall percentage of missingness for perception variables was 0.8%. Of the 46311 expected observations on symptoms and testing throughout the study period, 7498 were missing (16.2%). For the logistic (mixed) models missing data was ignored under the plausible assumption of missing at random, while for the generalised additive models for location scale and shape, it was omitted from the analyses. This was a suitable approach given that the amount of missing data was minimal, and the `gamlss` package only works with complete cases.

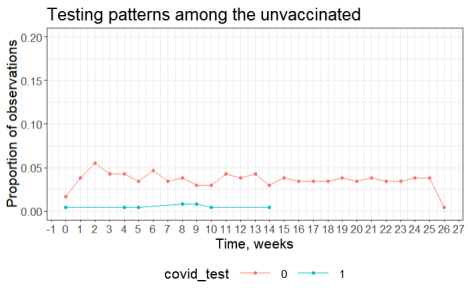


(a) Symptomatic

(b) Asymptomatic



(c) Vaccinated



(d) Unvaccinated

Figure 4: Testing patterns during winter by symptomatic and vaccination status

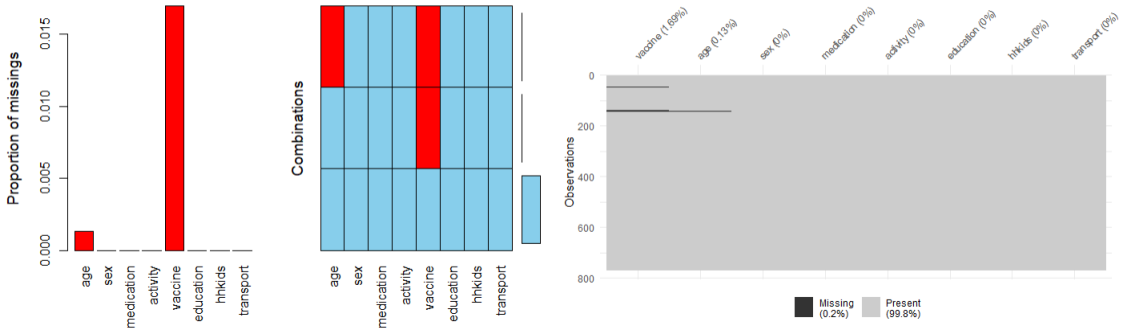


Figure 5: Missingness in baseline characteristics

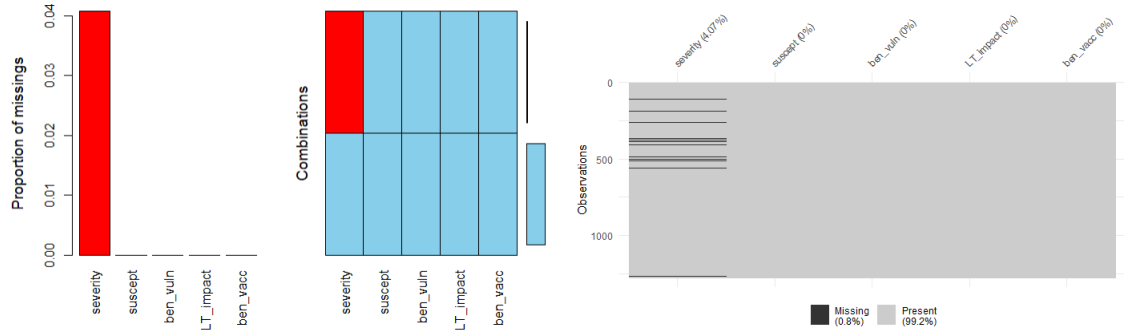


Figure 6: Missingness in perception variables. "severity" refers to perceived severity, "suscept" refers to perceived susceptibility, "ben_vuln" refers to perceived benefit to the vulnerable, "LT_impact" refers to long term impact and "ben_vacc" refers to perceived benefit of vaccination

5.2 Expected testing and isolation behaviour

Results of the expected testing and isolation behaviours of the participants are presented on Table 4. The adjusted odds ratios (OR) and 95% confidence intervals (CI) are presented. The model diagnostic

Table 4: Results of the logistic models for expected testing and isolation by vaccination status, contingency table analyses of expected testing by symptomatic status and the GAMLSS models for winter testing by vaccination and symptomatic status. Adjusted odds ratios and 95% confidence intervals (CI) are reported

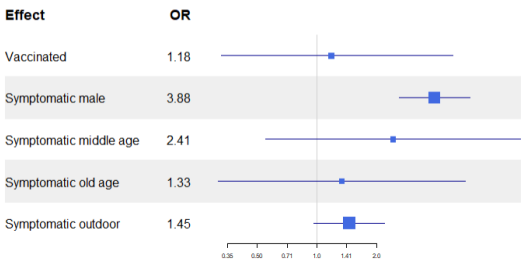
Variable	**Expected testing**	**Winter testing**	**Expected isolation**
	Odds ratio [CI]	*Odds ratio [CI]*	*Odds ratio [CI]*
Vaccination status			
Vaccinated	1.18 (0.33, 4.83)	0.78 (0.39, 1.55)	3.72 (0.69, 16.43)
Unvaccinated	-	-	-
Symptomatic status			
Symptomatic male	3.88 (2.59, 5.87)	2.46 (1.53, 3.95)	4.11 (2.03, 8.25)
Asymptomatic female	-	-	-
Symptomatic middle age	2.41 (0.55, 10.49)	9.38 (2.89, 30.43)	0.90 (0.08, 9.58)
Asymptomatic young	-	-	-
Symptomatic old	1.33 (0.32, 5.58)	18.62 (5.36, 64.70)	0.23 (0.02, 2.22)
Symptomatic outdoor	1.45 (0.96, 2.18)	1.93 (1.09, 3.42)	3.53 (1.97, 6.30)
Asymptomatic indoor	-	-	-

plots showed a good fit for the logistic models with standardised deviance residuals mostly below 3 in absolute value and all Cook's D values were below 0.1 (Appendix Figure 10). The expected odds for the vaccinated to test were insignificantly higher than for the unvaccinated (OR=1.18, CI: 0.33, 4.83). The interaction of symptomatic status and sex was significant demonstrating higher expected odds for symptomatic male to test than asymptomatic females (OR=3.88, CI:2.59, 5.87). Symptomatic middle-aged and old participants did not have significantly higher expected odds of testing than asymptomatic young (OR=2.41 CI:0.55, 10.49; OR=1.33 CI:0.32, 5.58). Symptomatic outdoor participants were also not expected to test significantly more than asymptomatic indoor participants (OR=1.45, CI:0.96, 2.18).

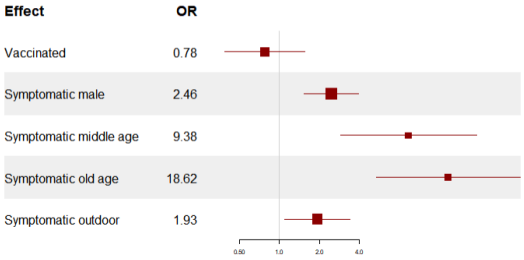
Similar to expectations on testing, the vaccinated had insignificant higher expected odds of isolating than the unvaccinated, and symptomatic male had significant higher odds of isolating than asymptomatic female (OR=3.72 CI:0.69, 16.43; OR=4.11 CI:2.03, 8.25). There were no significant differences in the expected isolation behaviour of the young, middle and old age groups. However, symptomatic outdoor participants were expected to isolate significantly more than asymptomatic indoor individuals (OR=3.53, CI:1.97, 6.30).

5.3 Actual testing performance during the winter

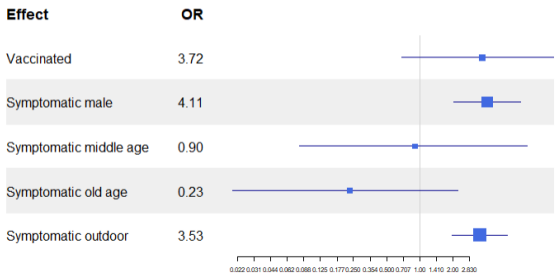
Results of the actual testing behaviour of participants during the winter are presented on Table 4. Diagnostic plots for the models reveal no signs of a lack of fit (Appendix Figures 11(a) and (b)). During the winter, there was no significant difference in the odds for the vaccinated and unvaccinated to test (OR=0.78, CI:0.39, 1.55). Symptomatic male had significant higher odds of testing than asymptomatic female (OR=2.46, CI: 1.53, 3.95). Similarly, symptomatic middle and old age participants had significantly higher odds of testing during the winter than asymptomatic young (OR=9.38 CI:2.89, 30.43; OR=18.62 CI:5.36, 64.70). Symptomatic outdoor participants also had significant higher odds of testing than asymptomatic indoor individuals during the winter (OR=1.93, CI:1.09,3.42). The random intercept variance for both models were 1.17 and 1.56, while the lambda smoothing parameters were 0.20 and 0.09 respectively. Interaction plots for symptomatic status by sex, age group and outdoor are presented on Figures 8(a), (b) and (c) respectively.



(a) Expected testing



(b) Winter testing



(c) Expected Isolation

Figure 7: Forest plots displaying odds ratios of expected versus winter testing and of expected isolation

5.4 Expected versus winter TI behaviour

A visual presentation of the results for expected versus winter testing as depicted on Figures 7(a) and (b), immediately portrays significantly higher odds of testing among the symptomatic relative to the asymptomatic during the winter than was expected. The odds for symptomatic male to test at baseline were 3.9 times the odds for asymptomatic female and in the winter this slightly dropped to 2.5 but yet still significant. Symptomatic middle and old age participants had baseline testing odds which were 2.4 and 1.3 times the odds for asymptomatic young respectively. During the winter, the odds increased to 9.4 and 18.6 times respectively. Furthermore, the expected testing odds for symptomatic outdoor participants were 45% higher than for asymptomatic indoor individuals but during the winter the odds increased and were 93% higher. Although insignificant, expected testing odds for the vaccinated went from 18% higher at baseline to 22% lower during the winter than the odds for the unvaccinated.

Re-visiting Figure 7(c) gives a picture of how participants were expected to isolate during the winter season. At a first glance, it is noted that the vaccinated were not expected to isolate significantly more than the unvaccinated, even though their expected odds to isolate were 3.7 times those of the unvaccinated. With regards to expected isolation by symptomatic status, there were mixed inconclusive findings with symptomatic male and outdoor participants having 4.1 and 3.5 times higher odds of isolating than asymptomatic female and indoor participants respectively. Meanwhile symptomatic middle and old age participants had 10% and 77% lower odds of expected isolation than asymptomatic young respectively.

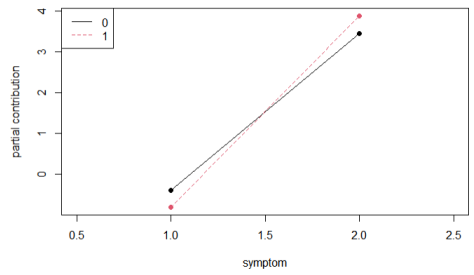
5.5 Association between testing behaviour and perceptions

Findings on the association between testing behaviour during the winter and COVID-19 perceptions are reported on Table 5. Diagnostic plots for all perception models indicate a good fit (Appendix Figures 11(c) to (g)). For easier understanding of the results, participants who agreed to a perception are considered to have a high perception, those who were neutral are considered to have a moderate perception and those who disagreed are considered to have a low perception. The interaction between perceived severity and medication status revealed mixed and inconclusive findings. Among participants taking medication, those with a moderate perceived severity had higher odds of testing while those with a high perceived severity had lower odds of testing than those who do not take medication and have a low perceived severity (OR=1.16 CI:0.78,1.74; OR=0.46 CI:0.28, 0.75). Highly educated

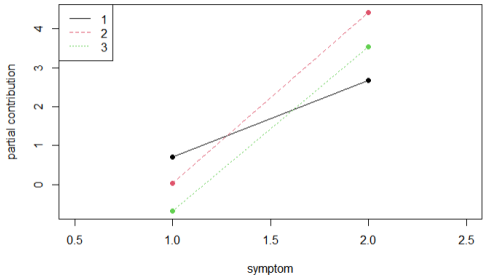
Table 5: Results of GAMLSS models on the association between testing and perceptions. Adjusted odds ratios (OR) and 95% confidence intervals (CI) are reported.

Perceptions	Categories	Adjusted OR (CI)
Perceived Severity	Agree and on medication	0.46 (0.28, 0.75)
	Disagree and not on medication	-
	Neutral and on medication	1.16 (0.78, 1.74)
	Agree and highly educated	0.93 (0.54, 1.62)
	Disagree and low to moderately educated	-
	Neutral and highly educated	0.48 (0.30, 0.77)
Perceived Susceptibility	Agree and on medication	0.39 (0.20, 0.74)
	Disagree and not on medication	-
	Neutral and on medication	0.48 (0.24, 0.93)
Perceived benefit to the vulnerable	Agree and on medication	1.47 (0.73, 3.00)
	Disagree and not on medication	-
	Neutral and on medication	2.80 (1.00, 7.80)
Perceived long term impact	Agree and highly educated	0.52 (0.28, 0.97)
	Disagree and not on medication	-
	Neutral and highly educated	0.31 (0.16, 0.62)
Perceived benefit of vaccination	Agree	7.24 (2.65, 19.83)
	Disagree	-
	Neutral	3.27 (1.13, 9.49)

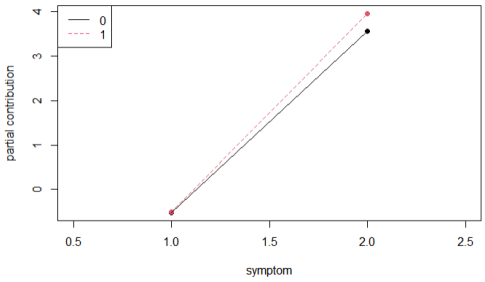
participants with moderate and high levels of perceived severity had lower odds of testing than the less educated with a low perception, but the results were inconclusive (OR=0.48 CI:0.30,0.77; OR=0.93 CI:0.54,1.62). The odds of testing were significantly lower for participants with moderate and high perceived susceptibility who are taking medications than for those with low perceived susceptibility who are not taking medications (OR=0.48 CI:0.24,0.93; OR=0.39 CI: 0.20,0.74). In other words, participants with moderate and high perceived susceptibility who take medication had respectively 52% and 61% lower odds of testing than those with low perceived susceptibility who do not take medication ($p = 0.03$, $p = 0.004$) (Appendix Table 14). Participants with moderate and high perceived benefit to the vulnerable who take medication had higher odds of testing than participants with a low perception who do not take medication (OR=2.80 CI: 1.00,7.80; OR=1.47 CI:0.73, 3.00), but the results were inconclusive. The interaction between perceived long term impact and education status was significant. It revealed that the less educated with a low perceived long term impact had higher odds of testing than the highly educated with moderate and high perceptions. The odds ratios of testing for moderate and high perceived long term impact among the highly educated relative to a low perceived long term impact among the less educated were respectively OR=0.31 CI:0.16,0.62 and OR=0.52 CI:0.28,0.97. In other words, the odds of testing among highly educated individuals with moderate and high perceived long term impact were respectively 69% and 48% lower than the odds for the less educated with a low perception ($p = 0.001$, $p = 0.04$) (Appendix Table 16). Participants with moderate and high perceived benefit of vaccination had significant higher odds of testing than those with a low perception (OR=3.27 CI:1.13,9.49; OR=7.24 CI:2.65,19.83). In more elaborate terms, the odds of testing among participants with moderate and high perceived benefit of vaccination were 3.3 and 7.2 times the odds for participants with a low perception respectively ($p = 0.03$, $p = 0.0001$) (Appendix Table 17). The random intercept variance for all perception models was 1.12, while the



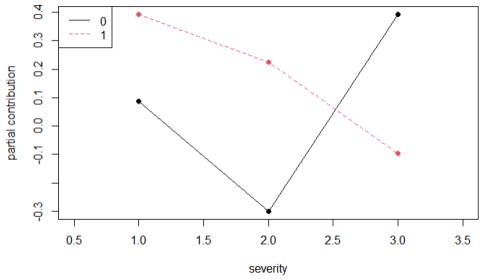
(a) Symptomatic status by sex



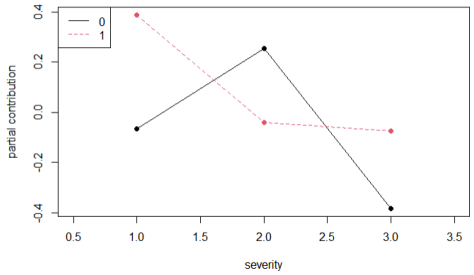
(b) Symptomatic status by age group



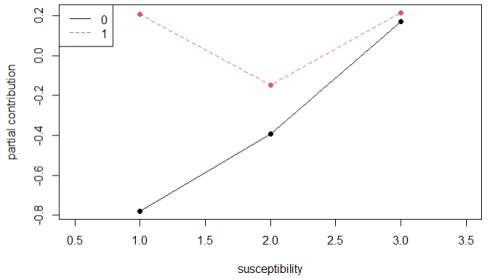
(c) Symptomatic status by outdoor



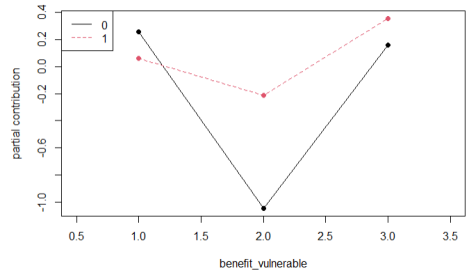
(d) Perceived severity by medication



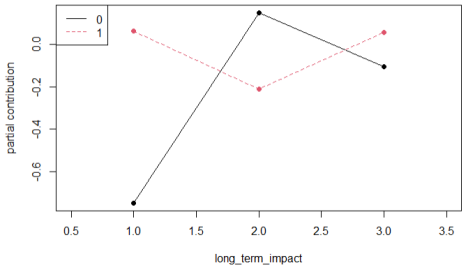
(e) Perceived severity by education



(f) Perceived susceptibility by medication



(g) Perceived benefit_vuln by medication



(h) Perceived LT_impact by education

Figure 8: Interaction plots for the GAMLSS models. "Benefit_vuln" refers to benefit to the vulnerable and "LT_impact" refers to long term impact.

lambda smoothing parameters were approximately 0.21. Applicable interaction plots for the perception models are displayed on Figures 8(d) to (h).

5.6 Sensitivity analysis

Results of the sensitivity analyses on testing and participation are presented on Table 6, alongside the original model results for comparative purposes. The diagnostic plots for both sensitivity models are shown on Appendix Figures 12 (a) and (b) and do not reveal any signs of a lack of fit. The sensitivity

analysis on testing produced in general more extreme results in terms of effect size and significance. Even the random effect variance was much larger compared to the original model and the lambda parameter was substantially smaller. Meanwhile the sensitivity analysis on participation yielded more similar results to the original model in every aspect.

Table 6: Adjusted odds ratios and 95% confidence intervals (CI) for the sensitivity models versus original model of winter testing by symptomatic status

	Sensitivity testing	**Sensitivity participation**	**Original model**
	Odds ratio [CI]	*Odds ratio [CI]*	*Odds ratio [CI]*
Symptomatic male	6.87 (5.07, 9.32)	2.59 (1.61, 4.17)	2.46 (1.53, 3.95)
Asymptomatic female	-	-	-
Symptomatic middle age	16.52 (6.85, 39.84)	6.54 (1.94, 22.05)	9.38 (2.89, 30.43)
Asymptomatic young	-	-	-
Symptomatic old	9.97 (4.03, 24.63)	13.00 (3.61, 46.86)	18.62 (5.36, 64.70)
Symptomatic outdoor	14.81 (10.40, 21.08)	1.95 (1.10, 3.45)	1.93 (1.09, 3.42)
Asymptomatic indoor	-	-	-
Random effect variance	6.12	1.62	1.56
Lambda parameter	0.03	0.08	0.09

6 Discussion and interpretation of results

6.1 Expected versus winter testing performance

In this study, testing habits and perceptions of participants on COVID-19 were obtained during the summer of 2022 to establish a baseline for interventions that focus on testing and isolation during the fall and winter seasons of 2022-2023. Participants were asked to state how they intend to test and isolate during the fall and winter seasons in order to understand their expected testing and isolation behaviour during these seasons. With the prolonged COVID-19 pandemic, there is a tendency that individuals may become fatigued and non compliant to testing and isolation protocols, which are very crucial during these seasons, to effectively manage a potential surge in Omicron subvariants of the SARS-CoV-2 virus. Having established baseline TI behaviour during the summer, it is necessary to assess this behaviour during the winter season. This comparison has been accomplished for testing behaviour but not for isolation behaviour, since there was no reliable data for isolation during the winter to enable such a comparison for isolation behaviour. The findings of expected isolation are however discussed as well in this section. Assessing TI behaviour during the winter enables the evaluation of the effectiveness of management interventions. This is important to identify loopholes in the interventions and to inform the strategies or potential modifications of future campaigns.

Symptomatic individuals had significantly higher odds of testing than the asymptomatic during the winter than was expected. This is a potential indication of the success of interventions in boosting testing behaviour among the symptomatic during the fall and winter seasons. This is because from baseline analysis on testing habits, the symptomatic did not have significantly higher expected odds of testing than the asymptomatic but in the winter analysis this distinction was significant. Specifically, symptomatic participants in the older age groups tested significantly more than the asymptomatic young in the winter contrary to baseline findings. The expected testing odds for the symptomatic middle-aged and old relative to asymptomatic young were increased 4 and 14 times respectively during the winter. Therefore, the pre-winter interventions potentially made many more middle-aged and old

participants to test than was estimated at baseline. This was crucial given the established higher risk of severe COVID-19 disease among the middle-aged and old, relative to the young[18]. Furthermore, testing and early intervention have been shown to be among the most important factors in preventing severe COVID-19 disease caused by delta and omicron SARS-CoV-2 variants[19]. Symptomatic outdoor participants were twice more likely to test during the winter than at baseline. This is yet another potential indicator of a positive outcome of management interventions, which is highly important in containing the spread of COVID-19 disease. Participants whose main activity is outdoors are more likely to be symptomatic, and a boost in their testing behaviour during the winter potentially contributed in controlling the spread of COVID-19 symptoms. Testing is a pre-cursor of isolation in the event of positive test results, and plays a crucial role in the management of COVID-19 infections. Thus, if symptomatic outdoor individuals test more and isolate in the event of an infection, it is very helpful to reduce the spread of the disease as they would stay isolated as opposed to going out as usual and potentially spreading the disease to more people. In general, winter testing was significantly associated with symptomatic status contrary to baseline findings, with the symptomatic testing more than the asymptomatic. This coincides with the results of a study on predictors of COVID-19 testing conducted in Canada[17], which found a significant association between testing and having COVID-19 symptoms. Although there was no significant difference in expected and winter testing for the vaccinated relative to unvaccinated, the results still indicate a potential behaviour modification among the unvaccinated. This is because at baseline the vaccinated tested more while during the winter the unvaccinated tested more. This is suggestive that the interventions successfully made more unvaccinated participants to test during the winter than was expected, which is a positive behaviour modification.

Even though the vaccinated had much higher odds to isolate at baseline, the distinction with the unvaccinated was insignificant. This could be because the confidence interval was based on Woolf's formula, which although it works quite well, is usually a bit conservative[8]. Likewise, there was no significant distinction in the expected isolation between the symptomatic and asymptomatic for the same potential reason. Male and outdoor participants with symptoms were expected to isolate significantly more than female and indoor participants without symptoms while, older participants with symptoms were expected to isolate insignificantly less than the young participants without symptoms. In effect, the vaccinated and symptomatic were not expected to isolate significantly differently from the unvaccinated and asymptomatic. Further investigation is required to assess expected isolation behaviour during fall and winter seasons which are more likely to experience a surge in subvariants of the SARS-CoV-2 virus.

6.2 Association between testing behaviour and perceptions

In addition to assessing the expected TI behaviour of participants during the winter, a secondary aim was to also investigate the association between TI behaviour and perceptions on COVID-19. This is important to identify perceptions that are negatively influencing TI behaviour and to explore misaligned associations between perceptions and TI behaviour. The findings can be used to guide and tailor future campaign strategies in order to achieve greater success.

The study revealed varied associations between testing behaviour and perceptions on COVID-19. Perceptions on susceptibility, long term impact and benefit of vaccination had a significant association with testing behaviour. Higher perceptions on susceptibility among individuals who take medication was negatively associated with testing behaviour relative to a low perception among individuals who do not take medication. A study investigating the relation between perception and behaviour in 1998[20], validated that perceptions have a direct and pervasive impact on overt behaviour. Based on this one would expect individuals with high perceived susceptibility to test more than those with low perceived susceptibility. However, findings of this study reveal the contrary, suggestive of a barrier between perception and testing behaviour among the highly susceptible. One such barrier could be fatigue given the prolonged nature of the pandemic. Furthermore, those with higher perceived susceptibility are those taking medication for other medical conditions, which could make them vulnerable to exhaustion in keeping up with TI protocols. Another potential explanation could be that the highly susceptible make fewer social contacts, and hence require less testing, since they are less likely to be symptomatic or infected. However, the previous study on the influence of risk perceptions on close contact frequency[1], found inconclusive results on the association between perceived susceptibility and the number of contacts. More investigation is required to explain barriers in the expected association between testing and perceived susceptibility.

Another key finding was that higher perceptions on long term impact among the highly educated were negatively associated with testing relative to a low perception among the less educated. The direction of this association is again contradictory to what is expected as previously discussed. This could be due to the fact that the less educated are often employed in jobs that involve frequent social contacts, and hence require frequent routine testing even though they have a low perception on long term impact. Meanwhile, highly educated individuals are more predisposed to work from home hence minimising social contacts and eliminating the need for frequent routine tests. This highlights the fact that perceptions are not always necessarily aligned with the expected behaviours, as there could be factors interfering with the association. Further investigation is needed to gain more insights on this. Furthermore, future campaigns should be targeted towards sensitizing the highly educated on the need for continuous compliance and adherence to testing protocols, which play a pivotal role in minimising the long term impact of the COVID-19 pandemic.

Higher perceptions on benefit of vaccination were positively associated with testing behaviour relative to a low perception. This points to an area of intervention on perception modification targeting individuals with a low perception on the benefit of vaccination. A successful modification of a low perception will encourage the individuals to test more, and increase the overall rates of testing. This in turn will lead to a more effective management of COVID-19 infections, which is crucial during the winter months with an often higher symptom burden.

Perceptions on severity and benefit to the vulnerable had inconclusive findings on their association with testing behaviour. The interaction effect of perceived severity and medication status was not only inconclusive but also revealed mixed findings. Similarly, the interaction between perceived severity and education status was inconclusive. Although adjusted interaction odds ratios for moderate and high perceived benefit to the vulnerable were suggestive of a positive association with testing, these findings were inconclusive. The aforementioned study[1], also had inconsistent findings on the association between perceived benefit to the vulnerable and number of social contacts, which is a behaviour that often precedes testing. As such, more investigation is also required to gain more insights on the association between perceived benefit to the vulnerable and testing. Likewise further research is needed to understand the association between perceived severity and testing.

The random intercept variance ranged between 1.12 and 1.56 for all GAMLSS models, indicating that between participant variability was not very large on average. This potentially indicates a not so strong correlation in the repeated measurements of each participant.

The sensitivity analysis on frequency of testing that excluded participants who tested less than 3 times, produced estimates that were in general larger with smaller standard errors and highly significant p values. This is not surprising because there were more repeated testing observations in the sensitivity dataset. On the other hand, including those who tested less than 3 times as in the original model, tends to dilute the effects resulting in smaller estimates. The sensitivity results indicate the importance of the longitudinal study, which gives more power to the analysis, when participants repeatedly test as intended over a long period of time. Although the results show that there is a huge gain in power and precision when subjects test repeatedly, they are potentially biased because they are based on a subset of compliant participants. Therefore, the results should not be used for final interpretations and conclusions.

The sensitivity analysis on frequency of participation produced results which are more similar to those obtained in the original model. The model estimates were very close and significance was not more extreme than in the original model. Even the random intercept variance and lambda parameter values were also very close. This indicates that the study results are robust to the inclusion of participants who completed less than 3 weekly questionnaires.

7 Drawbacks of used methodology

A pertinent limitation in modelling approaches that use the logit link is that, the resulting odds ratios tend to exaggerate the effect when the odds ratios are too far from 1. This is often so when the odds of an event (i.e. testing) in one category are very small, which is very likely when the sample size of that category is small. This scenario was experienced in this study and hence potentially resulted in some exaggerated odds ratios. However, the directionality of the effects remain unaffected.

The fact that there were few individuals in the unvaccinated and young age group categories of the survey participants resulted in small strata for the respective variables. This situation is known to

cause large standard errors, wide confidence intervals and imprecise model estimates. In some cases it can also affect the significance of the results, since a wider confidence interval is more likely to include the null value of the odds ratio. In consequence, the estimated odds ratios pertaining to the aforementioned variables were subject to these potential drawbacks.

In the absence of a survey design with probability sampling, a design-based analysis which incorporates weights and provincial strata was not possible. With such a design and its related analysis, everyone in the sample frame of Belgium is given an equal inclusion probability, and the study findings tend to be generalisable to the entire population of Belgium.

Given the observational nature of the study, confounding is an obvious problem which was addressed during the analyses but not exhaustively. There is often some residual unadjusted confounding from unknown and/or unmeasured confounders. However, the most important known potential confounders were all adjusted in the analyses giving a good control of the confounder situation.

There was a drawback at the level of the weekly questionnaire design which collected information on general preventive measures after an infection, and not specifically for isolation. As a result, a winter analysis on isolation behaviour under (un)vaccinated and (a)symptomatic conditions was not possible. Another limitation is that data for the month of March 2023 was not incorporated in the analysis due to late availability. This leads to a loss of information on testing behaviour during the entire winter period.

8 Ethics, societal relevance and stakeholders

In this project all participants 18 years and above with internet access voluntarily sign up into the platform with an email address and password. Once signed up, they have access to all the information they need to know and register through the completion of a form with baseline characteristics to join the study. Younger individuals are enrolled through the account of their parent or legal guardian who in turn acts to complete the weekly questionnaires on their behalf. Infectieradar.be system has been carefully tested by external parties at the University of Hasselt to ensure the security and privacy of the personal data of enrolled participants[3]. Participants are notified that they can participate in the survey for as long as they want. However, if they wish to discontinue they just need to stop responding to the weekly emails or withdraw completely by closing their account through the settings. The data received was well processed to remove any personal identifiable information of the participants to further ensure data privacy. The study is also of an observational nature where no randomisation is done, since it is unethical to randomise participants to be unvaccinated or to be symptomatic in order to assess testing performance. Thus, the ethical aspects of autonomy, privacy and beneficence are well preserved in the design implementation of the survey. The use of accurate statistical tools and methodology to analyse the data was ensured to further incorporate the ethical aspect of beneficence.

This study is undoubtedly of great societal relevance given that citizens of various countries, including Belgium, have had to endure severe restrictions and closures during major waves of the COVID-19 pandemic. Many people died[1,12,13,14,15], others suffered severe morbidity[15,16] with hospitalisation and urgent care, while some suffered frequent episodes and absences from work due to isolation requirements. Some individuals lost their source of livelihood altogether due to the socio-economic impact of the harsh waves[15,16]. The severe restrictions and lock downs had a heavy toll on the mental health of some individuals with a remarkable rise in the number of people diagnosed with anxiety and depression[14,15,16], among other mental health diagnoses. Stringent travel requirements made travelling more expensive and complicated affecting the quality of life of many, and the list goes on. Given that morbidity and mortality rates are more likely to spike during the winter season with re-surging subvariants, it is of great importance to ensure that individuals remain compliant to prescribed TI protocols during this period, to help contain the spread of the subvariants. In the absence of adherence to these protocols, the wave could go out of control leading to more severe restrictions and closures, which in turn affect the economy and the mental health of individuals. Therefore, this study which aims at assessing TI behaviour during winter months, can assess adherence to TI protocols during this peak season and evaluate the effectiveness of management interventions. The study can also identify perceptions that are negatively associated with TI behaviour. The findings can inform future public health strategies that focus on boosting TI behaviours during the winter months, and lead to a more successful and sustained control of potential waves during winter. This in turn could reduce morbidity and mortality rates of COVID-19 infections during the winter, reduce the need for severe restrictions

and prolonged closures, and minimise their associated negative impact on the society. In effect, it could result in a healthier society with a better quality of life, especially during the winter months when these elements of well being are highly threatened by potential waves of the pandemic.

The stakeholders in this study are primarily the citizens as any decisions made as a result of this study have a direct impact on their lives. For instance, any potential modification of the current protocols will obviously be reflected on the lives of the citizens. The ministry of health and other public health agencies are also key stakeholders since the survey findings will potentially inform further decisions they make with regards to the management of COVID-19. Whether they will be disbursing funds for a new campaign aimed at modifying perceptions found to be barriers to the implementation of management protocols, or fortifying the current protocols, depends on the findings of the survey. Hence they are a major stakeholder of this study. Another major stakeholder is the University of Hasselt which is a part of the Influenzanet partnership constituting various European universities and Government agencies, under whose platform this survey is being conducted. The survey findings will therefore inform which pertinent research areas are conclusive and which ones require further research. This therefore makes the University of Hasselt under Influenzanet partnership a major stakeholder.

9 Conclusion

The main aim of this study was to assess the expected performance of testing and isolation (TI) during the fall and winter seasons of 2022-2023 in Belgium. The secondary aim was to investigate the association between TI behaviour and perceptions on COVID-19. However, due to the unavailability of reliable isolation data during the winter, it was neither possible to assess the expected performance of isolation during the winter, nor to analyse the association between isolation behavior and perceptions. Nonetheless, an analysis of the expected isolation behaviour was conducted and the findings were reported. Expected TI behaviour was analysed through logistic regression models and contingency tables. Generalized additive models for location scale and shape were implemented to analyse testing behaviour during the winter and the association between TI behaviour and perceptions.

The study found that testing behaviour during the winter was significantly more extreme than was expected among the symptomatic relative to asymptomatic, indicative of successful pre-winter campaigns that focused on testing and isolation. No significant distinction was found in the testing performance of the vaccinated relative to the unvaccinated both at baseline and during the winter. Analyses on the association between testing and perceptions unveiled that high perceptions did not necessarily align with the desired behaviour as expected. It was established that high perceptions on susceptibility and long term impact were negatively associated with testing, while high perceptions on benefit of vaccination were positively associated with testing behaviour. Further research is required to explore factors that explain and/or barriers that distort a positive association between high perceptions on susceptibility and long term impact, and testing behaviour. Future campaigns should target the highly educated and sensitize them on the importance of continuous adherence to testing protocols in order to alleviate potential long term impacts of the COVID-19 pandemic. Campaign interventions should also be tailored to modify low perceptions on the benefit of vaccination which were found to have a negative association with testing behaviour. Perceptions on severity and benefit to the vulnerable were inconclusive in their association with testing behaviour and should be further investigated.

10 Recommendations for future research

Given that the research questions were not exhaustively answered due to a lack of reliable data on isolation during the winter, it is recommended to do further research in this area to understand how perceptions are associated with isolation behaviour, and assess expected isolation behaviour during potential peak seasons. Isolation of infected persons is a very important behavioural component in the management of COVID-19, as such the continual monitoring and assessment of its implementation remains of high public health importance. It is also recommended to do a comparative multi-country analysis which can highlight countries with better success outcomes, reflecting more effective management strategies which can be emulated. Based on study results, further research is required to understand how perceptions on severity and benefit to the vulnerable are associated with testing. More research is also needed to investigate factors influencing adherence to other COVID-19 mitiga-

tion behaviours like hand sanitation and masking, which together with testing, isolation and social distancing, play a vital role in the non pharmaceutical management of the COVID-19 disease. Continuous adherence to these behaviours helps to contain the spread of the disease, and this is even more crucial during peak seasons with a potential emergence of new subvariants.

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Conflict of Interest *The author declares no conflict of interest.*

Appendix A: Important R codes

```
/*Logistic model for expected proportion of testing by vaccination status*/

mod2 <- glm(test ~ vacc + age_grp + sex + med + Educ_high, data = baseline_habits2, family = "binomial")
summary(mod2)
model2_data <- augment(mod2) %>%
  mutate(index = 1:n())

ggplot(model2_data, aes(index, .std.resid), color = ) +
  geom_point(alpha = .5) +
  geom_ref_line(h = 3)

  model2_data %>%
  filter(abs(.std.resid) > 3)

plot(mod2, which = 4, id.n = 5)

influencePlot(mod2, col="red", id.n=3)
outlierTest(mod2)

/*Logistic model for expected proportion of isolation by vaccination status*/

mod4 <- glm(isolation ~ vacc + age_grp + sex + med + Educ_high, data = baseline_habits2, family = "binomial")
summary(mod4)

model4_data <- augment(mod4) %>%
  mutate(index = 1:n())

ggplot(model4_data, aes(index, .std.resid)) +
  geom_point(alpha = .5) +
  geom_ref_line(h = 3)

model4_data %>%
  filter(abs(.std.resid) > 3)
plot(mod4, which = 4, id.n = 5)
influencePlot(mod4, col="red", id.n=3)
outlierTest(mod4)

/*Logistic mixed model for winter testing by vaccination status*/

mod2 <- glmer(covid_test ~ vaccination_status + Educ_high + med + sex + week + age_group +
(1| participantID), data = test_datav2, family = binomial,
control = glmerControl(optimizer = "bobyqa"), nAGQ = 10)
summary(mod2, corr = F)

/*Logistic mixed model for winter testing by symptomatic status*/

mod2 <- glmer(covid_test~week + symptom*sex + symptom*age_grp +
outdoor + public_transp + (1|participantID),test_datav2, family = binomial,
control = glmerControl(optimizer = "bobyqa"), nAGQ = 10)
summary(mod2)


/*GAMLSS model for winter testing by vaccination status*/

m3<-gamlss(covid_test~vaccination_status + sex*pb(week) +
age_grp*pb(week) + med + Educ_high +  random(as.factor(participantID)),
family = BI, data = na.omit(test_datav2))
summary(m3)
summary_mod <- exp(cbind(OR = coef(m3), confint(m3)))
```

```
summary_mod
getSmo(m3)
plot(m3)

/*GAMLSS model for winter testing by symptomatic status*/

m3<-gamlss(covid_test~pb(week) + symptom*sex + symptom*age_grp +
symptom*outdoor  + public_transp +  random(as.factor(participantID)),
family = BI, data = na.omit(test_datav2))
summary(m3)
summary_mod <- exp(cbind(OR = coef(m3), confint(m3)))
summary_mod
getSmo(m3)
plot(m3)
plot2way(m3, c("symptom","sex"))
plot2way(m3, c("symptom","age_grp"))
plot2way(m3, c("symptom","outdoor"))

/*GAMLSS model for the influence of perceived severity on testing*/

m3<-gamlss(covid_test~pb(week)*sex + pb(week)*age_grp +
severity*med + severity*Educ_high + random(as.factor(participantID)),
family = BI, data = na.omit(test_datap7))
summary(m3)
summary_mod <- exp(cbind(OR = coef(m3), confint(m3)))
summary_mod
getSmo(m3)
plot(m3)
plot2way(m3, c("severity","med"))
plot2way(m3, c("severity","Educ_high"))

/*GAMLSS model for the influence of perceived susceptibilty on testing*/

m3<-gamlss(covid_test~ susceptibility + pb(week)*sex + pb(week)*age_grp +
susceptibility*med + Educ_high + random(as.factor(participantID)),
family = BI, data = na.omit(test_datap7))
summary(m3)
summary_mod <- exp(cbind(OR = coef(m3), confint(m3)))
summary_mod
getSmo(m3)
plot(m3)
plot2way(m3, c("susceptibility","med"))

/*GAMLSS model for the influence of perceived benefit to the vulnerable on testing*/

m3<-gamlss(covid_test~pb(week)*sex + pb(week)*age_grp +
benefit_vulnerable*med + Educ_high + random(as.factor(participantID)),
family = BI, data = na.omit(test_datap7))
summary(m3)
summary_mod <- exp(cbind(OR = coef(m3), confint(m3)))
summary_mod
getSmo(m3)
plot(m3)
plot2way(m3, c("benefit_vulnerable","med"))

/*GAMLSS model for the influence of perceived long term impact on testing*/

m3<-gamlss(covid_test~ pb(week)*sex + pb(week)*age_grp + med +
long_term_impact*Educ_high + random(as.factor(participantID)),
family = BI, data = na.omit(test_datap7),  control = gamlss.control(n.cyc = 20))
summary(m3)
summary_mod <- exp(cbind(OR = coef(m3), confint(m3)))
```

```
summary_mod
getSmo(m3)
plot(m3)
plot2way(m3, c("long_term_impact","Educ_high"))

/*GAMLSS model for the influence of perceived benefit of vaccination on testing*/

m3<-gamlss(covid_test~benefit_vacc + pb(week)*sex + pb(week)*age_grp +
med + Educ_high + random(as.factor(participantID)),
family = BI, data = na.omit(test_datap7))
summary(m3)
summary_mod <- exp(cbind(OR = coef(m3), confint(m3)))
summary_mod
getSmo(m3)
plot(m3)
```

Appendix B: Tables and Figures

Table 7: Data pre-processing; coding variables from raw data

Variable	Raw data (options)	Coding
test	Derived from (a)symptomatic testing variables	1 = Yes, 0 = No
isolation	Derived from (a)symptomatic isolation variables	1 = Yes, 0 = No
cov_test	'Blood', 'PCR', 'Rapid'	1 = Yes
	'Unknown' (did not test or don't know)	0 = No
vacc	'Yes'	vacc1=vaccinated
	'No accept invitation', 'No decline invitation' 'No will accept invitation', 'No will decline invitation' 'Unknown'	vacc0 = unvaccinated
symptom	'True'	symptom1= had symptoms
	'False'	symptom0 = had no symptoms
sex	'Male'	sex1=male
	'Female'	sex0 = female
	'Undefined'	2 participants - excluded
age_grp	Age range 1-85 years	age_grp1=1-29 years age_grp2 = 30-59 years age_grp3 = 60-89 years
med	'True'	med1=on medication
	'False'	med0 = not on medication
outdoor	'Attending daycare, school, college or university' 'Paid employment, full-time' 'Paid employment, part-time' 'Self-employed'	outdoor1=main activity outdoor
	'Home-maker', 'Retired', 'Unemployed' 'I am technically unemployed due to the COVID-19 epidemic' 'Long-term sickleave or parental leave', 'Other'	outdoor0=main activity indoor
Educ_high	'professional or academic bachelor grade' 'master or PhD grade'	Educ_high1=high
	'grade of primary school' 'grade of secondary school (all three cycles)' 'grade of secondary school until second cycle' 'no formal qualifications'	Educ_high0=low to moderate
	'prefer not to answer'	treated as missing data
Public_transp	Public transportation	Public_transp1=public transport
	'Walking', 'Bike', 'Motorbike/scooter','Car', 'Other'	Public_transp0=private transport
week	Derived from the date variable	ranges from 0-26 weeks
symp_test	'very likely, 'fairly likely'	1 = Yes
	'fairly unlikely', 'very unlikely'	0 = No
asymp_test	'more than once per week', 'once per week', 'every two weeks' 'once per month', 'less than once per month'	1 = Yes
	'never', 'I don't know'	0 = No
symp_iso	'very likely, 'fairly likely'	1 = Yes
	'fairly unlikely', 'very unlikely'	0 = No
asymp_iso	'very likely, 'fairly likely'	1 = Yes
	'fairly unlikely', 'very unlikely'	0 = No

Table 8: Baseline summary statistics by vaccination status

	unvaccinated	vaccinated	Overall
	(N=11)	(N=732)	(N=756) (Missing=13)
Sex			
Female	7 (63.6%)	427 (58.3%)	442 (58.5%)
Male	4 (36.4%)	305 (41.7%)	314 (41.5%)
Age group (years)			
1-29	0 (0%)	20 (2.7%)	21 (2.8%)
30-59	5 (45.5%)	294 (40.2%)	304 (40.2%)
60-89	6 (54.5%)	418 (57.1%)	430 (56.9%)
Missing	0 (0%)	0 (0%)	1 (0.1%)
Medication			
No	8 (72.7%)	333 (45.5%)	348 (46.0%)
Yes	3 (27.3%)	399 (54.5%)	408 (54.0%)
HH_kids			
No	10 (90.9%)	609 (83.2%)	627 (82.9%)
Yes	1 (9.1%)	123 (16.8%)	129 (17.1%)
Public_transp			
No	11 (100%)	696 (95.1%)	720 (95.2%)
Yes	0 (0%)	36 (4.9%)	36 (4.8%)
Educ_high			
Preferred not to answer	0 (0%)	6 (0.8%)	6 (0.8%)
No	4 (36.4%)	190 (26.0%)	197 (26.1%)
Yes	7 (63.6%)	536 (73.2%)	553 (73.1%)
Outdoor			
No	4 (36.4%)	400 (54.6%)	410 (54.2%)
Yes	7 (63.6%)	332 (45.4%)	346 (45.8%)
Province			
Antwerpen	5 (45.5%)	306 (41.8%)	312 (41.3%)
Limburg	1 (9.1%)	154 (21.0%)	161 (21.3%)
Oost-Vlaanderen	2 (18.2%)	89 (12.2%)	92 (12.2%)
Vlaams-Brabant	2 (18.2%)	94 (12.8%)	99 (13.1%)
Brussel	0 (0%)	12 (1.6%)	12 (1.6%)
Henegouwen	0 (0%)	3 (0.4%)	4 (0.5%)
Luik	0 (0%)	3 (0.4%)	3 (0.4%)
Luxemburg	0 (0%)	1 (0.1%)	1 (0.1%)
Namen	0 (0%)	2 (0.3%)	2 (0.3%)
Waals-Brabant	0 (0%)	3 (0.4%)	3 (0.4%)
West-Vlaanderen	0 (0%)	52 (7.1%)	53 (7.0%)
Missing	1 (9.1%)	13 (1.8%)	14 (1.9%)

Table 9: Results of logistic regression for expected testing by vaccination status. Odds ratios (OR) and their 95% lower (LCL) and upper confidence limits (UCL) have been presented

	Estimate	Std. Error	z value	P value	OR	95% LCL	95% UCL
(Intercept)	0.61	0.85	0.72	0.47	1.85	0.33	9.81
vacc1	0.17	0.67	0.25	0.80	1.18	0.33	4.83
age_grp2	-1.27	0.52	-2.45	0.01	0.28	0.09	0.75
age_grp3	-2.11	0.51	-4.12	< 0.0001	0.12	0.04	0.32
sex1	1.05	0.15	7.00	< 0.0001	2.85	2.13	3.82
med1	-0.41	0.16	-2.65	0.01	0.66	0.49	0.90
Educ_high1	-0.12	0.18	-0.66	0.51	0.89	0.63	1.26

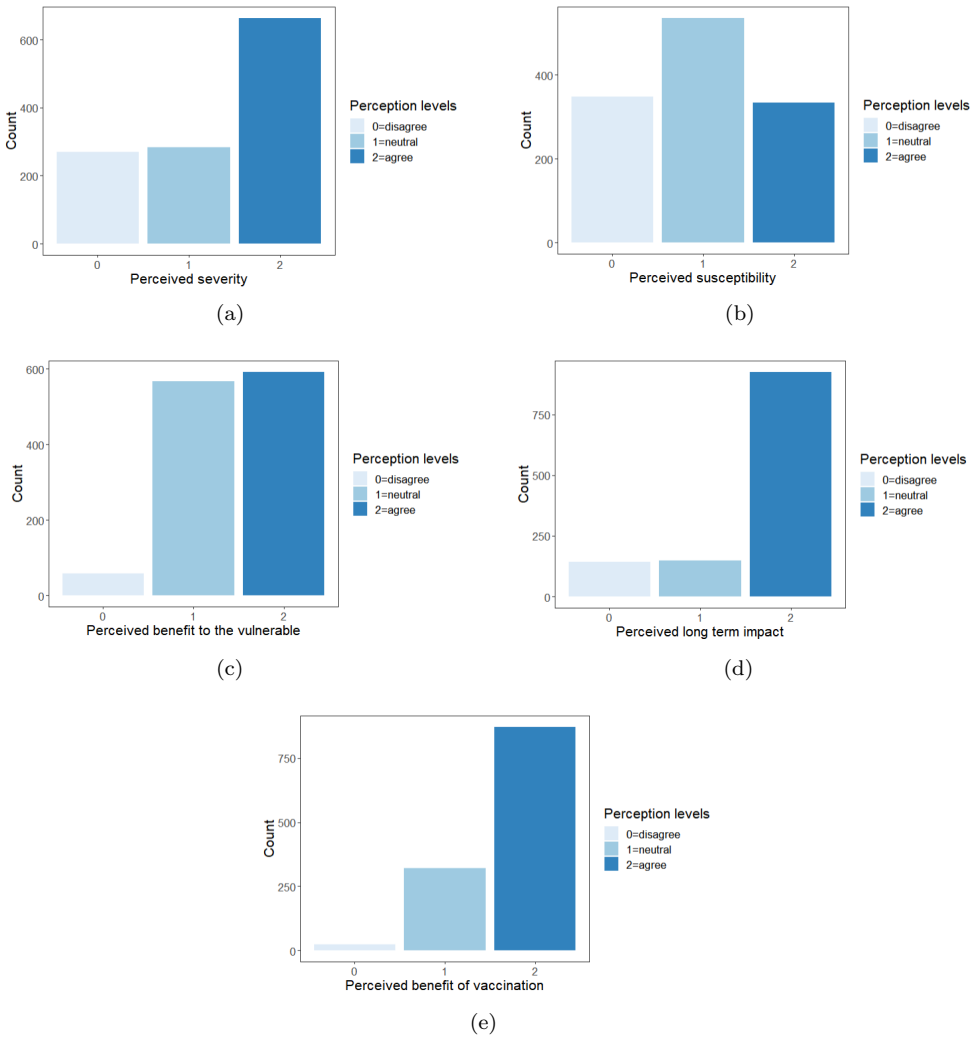
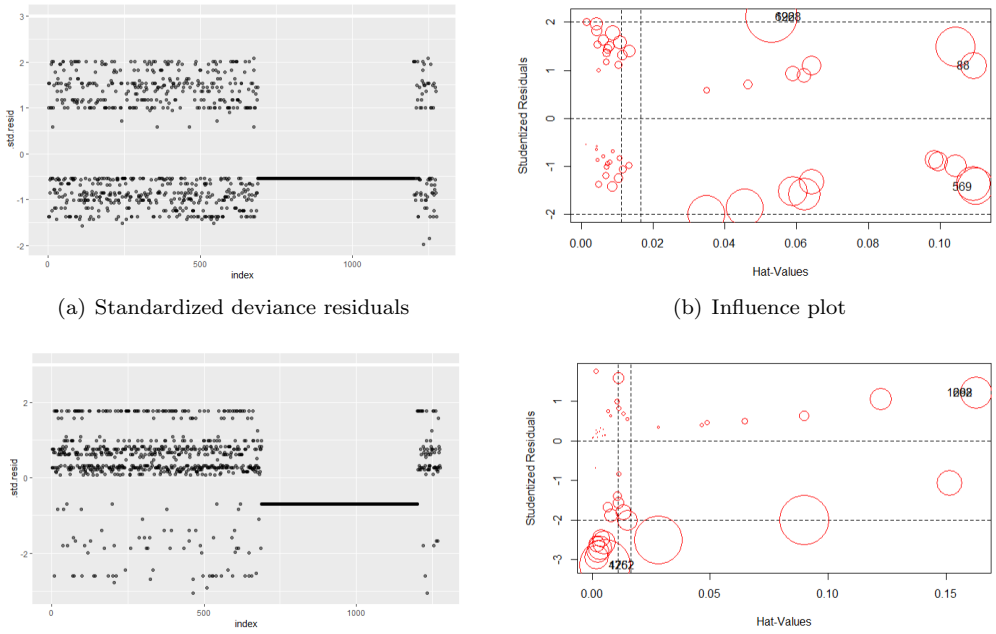


Figure 9: Distribution of participants by perception category for all perception variables.

Table 10: Results of logistic regression for expected isolation by vaccination status. Odds ratios (OR) and their 95% lower (LCL) and upper confidence limits (UCL) have been presented

	Estimate	Std. Error	z value	P value	OR	95% LCL	95% UCL
(Intercept)	3.58	1.08	3.31	< 0.0001	35.70	4.66	338.47
vacc1	1.31	0.79	1.67	0.10	3.72	0.69	16.43
age_grp2	-1.29	0.74	-1.74	0.08	0.27	0.05	1.08
age_grp3	-1.72	0.72	-2.40	0.02	0.18	0.04	0.67
sex1	2.44	0.20	12.21	< 0.0001	11.49	7.84	17.19
med1	-1.79	0.22	-8.17	< 0.0001	0.17	0.11	0.25
Educ_high1	-2.70	0.30	-9.04	< 0.0001	0.07	0.04	0.12



(a) Standardized deviance residuals

(b) Influence plot

(c) Standardized deviance residuals

(d) Influence plot

Figure 10: Diagnostic plots for models of expected testing (upper) and expected isolation (lower) by vaccination status

Table 11: Results of GAMLSS model for winter testing by vaccination status. Odds ratios (OR) and their 95% lower (LCL) and upper confidence limits (UCL) are presented

	Estimate	Std. Error	P value	OR	95% LCL	95% UCL
(Intercept)	-3.12	0.60	< 0.0001	0.04	0.01	0.14
vacc1	-0.25	0.35	0.47	0.78	0.39	1.55
sex1	0.90	0.18	< 0.0001	2.46	1.72	3.52
pb(week)	-0.10	0.045	0.03	0.91	0.83	0.99
age_grp2	-0.69	0.49	0.16	0.50	0.19	1.31
age_grp3	-1.35	0.49	0.006	0.26	0.10	0.67
med1	0.17	0.09	0.07	1.18	0.99	1.41
Educ_high1	0.22	0.11	0.04	1.24	1.01	1.54
sex1:pb(week)	-0.03	0.01	0.01	0.97	0.94	0.99
pb(week):age_grp2	0.11	0.046	0.015	1.12	1.02	1.22
pb(week):age_grp3	0.10	0.046	0.03	1.10	1.01	1.21

Table 12: Results of GAMLSS model for winter testing by symptomatic status. Odds ratios (OR) and their 95% lower (LCL) and upper confidence limits (UCL) are presented

	Estimate	Std. Error	P value	OR	95% LCL	95% UCL
(Intercept)	-4.37	0.46	< 0.0001	0.01	0.01	0.03
pb(week)	-0.04	0.007	< 0.0001	0.96	0.95	0.97
symptom1	0.96	0.65	0.14	2.61	0.73	9.32
sex1	-0.41	0.20	0.045	0.66	0.45	0.99
age_grp2	-0.68	0.41	0.09	0.51	0.23	1.13
age_grp3	-1.38	0.44	0.002	0.25	0.11	0.60
outdoor1	0.01	0.25	0.97	1.01	0.62	1.65
public_transp1	0.14	0.22	0.55	1.15	0.74	1.77
symptom1:sex1	0.90	0.24	0.0002	2.46	1.53	3.95
symptom1:age_grp2	2.24	0.60	0.0002	9.38	2.89	30.43
symptom1:age_grp3	2.92	0.64	< 0.0001	18.62	5.36	64.70
symptom1:outdoor1	0.66	0.29	0.024	1.93	1.09	3.42

Table 13: Results of GAMLSS model for the association between testing and perceived severity. Odds ratios (OR) and their 95% lower (LCL) and upper confidence limits (UCL) are presented

	Estimate	Std. Error	P value	OR	95% LCL	95% UCL
(Intercept)	-3.57	0.52	< 0.0001	0.03	0.01	0.08
pb(week)	-0.10	0.045	0.028	0.91	0.83	0.99
sex1	0.91	0.18	< 0.0001	2.49	1.74	3.55
age_grp2	-0.63	0.49	0.19	0.53	0.20	1.38
age_grp3	-1.29	0.49	0.01	0.27	0.11	0.71
severity1	0.22	0.26	0.40	1.24	0.75	2.06
severity2	0.36	0.31	0.24	1.43	0.79	2.61
med1	0.31	0.14	0.03	1.36	1.02	1.80
Educ_high1	0.46	0.18	0.013	1.58	1.10	2.26
pb(week):sex1	-0.03	0.013	0.013	0.97	0.94	0.99
pb(week):age_grp2	0.11	0.046	0.014	1.12	1.02	1.22
pb(week):age_grp3	0.10	0.046	0.03	1.10	1.01	1.21
severity1:med1	0.15	0.21	0.46	1.16	0.78	1.74
severity2:med1	-0.79	0.25	0.002	0.46	0.28	0.75
severity1:Educ_high1	-0.74	0.24	0.003	0.48	0.30	0.77
severity2:Educ_high1	-0.07	0.28	0.81	0.93	0.54	1.62

Table 14: Results of GAMLSS model for the association between testing and perceived susceptibility. Odds ratios (OR) and their 95% lower (LCL) and upper confidence limits (UCL) are presented

	Estimate	Std. Error	P value	OR	95% LCL	95% UCL
(Intercept)	-4.11	0.56	< 0.0001	0.02	0.01	0.05
susceptibility1	0.39	0.29	0.19	1.47	0.83	2.62
susceptibility2	0.95	0.28	0.0006	2.59	1.50	4.48
pb(week)	-0.10	0.045	0.028	0.90	0.83	0.99
sex1	0.86	0.18	< 0.0001	2.35	1.65	3.36
age_grp2	-0.59	0.49	0.22	0.55	0.21	1.44
age_grp3	-1.19	0.49	0.014	0.30	0.12	0.79
med1	0.99	0.31	0.001	2.69	1.48	4.89
Educ_high1	0.12	0.11	0.24	1.13	0.92	1.40
pb(week):sex1	-0.03	0.01	0.01	0.97	0.94	0.99
pb(week):age_grp2	0.11	0.045	0.013	1.12	1.02	1.23
pb(week):age_grp3	0.10	0.046	0.03	1.10	1.01	1.21
susceptibility1:med1	-0.74	0.34	0.03	0.48	0.24	0.93
susceptibility2:med1	-0.94	0.33	0.004	0.39	0.20	0.74

Table 15: Results of GAMLSS model for the association between testing and perceived benefit to the vulnerable. Odds ratios (OR) and their 95% lower (LCL) and upper confidence limits (UCL) are presented

	Estimate	Std. Error	P value	OR	95% LCL	95% UCL
(Intercept)	-3.30	0.54	< 0.0001	0.04	0.01	0.11
pb(week)	-0.10	0.045	0.03	0.91	0.83	0.99
sex1	0.86	0.18	< 0.0001	2.37	1.66	3.39
age_grp2	-0.60	0.49	0.22	0.55	0.21	1.42
age_grp3	-1.29	0.49	0.008	0.28	0.11	0.72
benefit_vulnerable1	-1.30	0.39	0.001	0.27	0.13	0.59
benefit_vulnerable2	-0.095	0.24	0.69	0.91	0.57	1.46
med1	-0.19	0.35	0.58	0.83	0.41	1.64
Educ_high1	0.20	0.11	0.05	1.22	1.00	1.50
pb(week):sex1	-0.03	0.013	0.013	0.97	0.94	0.99
pb(week):age_grp2	0.11	0.046	0.014	1.12	1.02	1.22
pb(week):age_grp3	0.10	0.046	0.03	1.10	1.01	1.21
benefit_vulnerable1:med1	1.03	0.52	0.05	2.80	1.00	7.80
benefit_vulnerable2:med1	0.39	0.36	0.28	1.47	0.73	3.00

Table 16: Results of GAMLSS model for the association between testing and perceived long term impact. Odds ratios (OR) and their 95% lower (LCL) and upper confidence limits (UCL) are presented

	Estimate	Std. Error	P value	OR	95% LCL	95% UCL
(Intercept)	-3.95	0.55	< 0.0001	0.02	0.01	0.06
pb(week)	-0.10	0.045	0.028	0.91	0.83	0.99
sex1	0.87	0.18	< 0.0001	2.40	1.68	3.43
age_grp2	-0.65	0.49	0.18	0.52	0.20	1.36
age_grp3	-1.36	0.49	0.005	0.26	0.10	0.67
med1	0.16	0.09	0.08	1.18	0.98	1.41
long_term_impact1	0.90	0.32	0.005	2.45	1.31	4.57
long_term_impact2	0.64	0.29	0.025	1.90	1.08	3.33
Educ_high1	0.81	0.28	0.004	2.25	1.29	3.92
pb(week):sex1	-0.03	0.013	0.013	0.97	0.94	0.99
pb(week):age_grp2	0.11	0.046	0.013	1.12	1.02	1.22
pb(week):age_grp3	0.10	0.046	0.03	1.10	1.01	1.21
long_term_impact1:Educ_high1	-1.17	0.35	0.001	0.31	0.16	0.62
long_term_impact2:Educ_high1	-0.65	0.31	0.04	0.52	0.28	0.97

Table 17: Results of GAMLSS model for the association between testing and perceived benefit of vaccination. Odds ratios (OR) and their 95% lower (LCL) and upper confidence limits (UCL) are presented

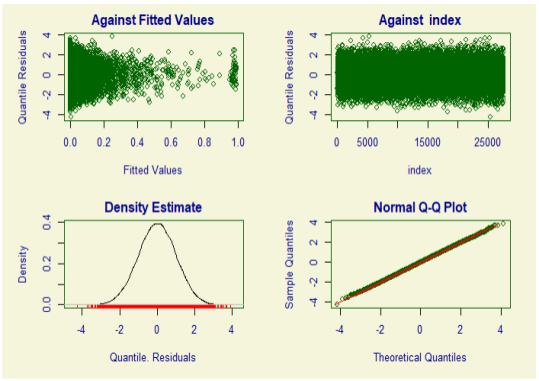
	Estimate	Std. Error	P value	OR	95% LCL	95% UCL
(Intercept)	-5.30	0.71	< 0.0001	0.00	0.00	0.02
benefit_vacc1	1.19	0.54	0.03	3.27	1.13	9.49
benefit_vacc2	1.98	0.51	0.0001	7.24	2.65	19.83
pb(week)	-0.10	0.045	0.03	0.91	0.83	0.99
sex1	0.90	0.18	< 0.0001	2.47	1.73	3.52
age_grp2	-0.51	0.49	0.30	0.60	0.23	1.57
age_grp3	-1.29	0.49	0.009	0.28	0.11	0.72
med1	0.12	0.09	0.20	1.13	0.94	1.35
Educ_high1	0.14	0.11	0.18	1.15	0.94	1.41
pb(week):sex1	-0.03	0.013	0.013	0.97	0.94	0.99
pb(week):age_grp2	0.11	0.046	0.014	1.12	1.02	1.22
pb(week):age_grp3	0.10	0.046	0.03	1.10	1.01	1.21

Table 18: Results of sensitivity analysis for winter testing by symptomatic status excluding those who tested less than 3 times

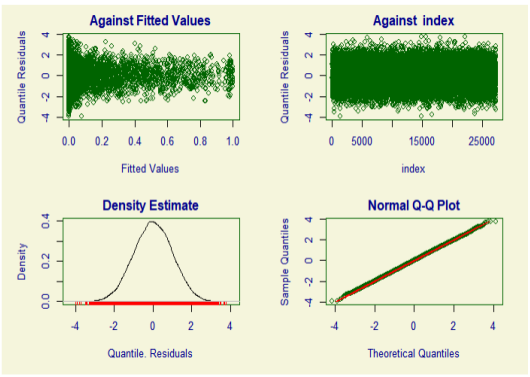
	Estimate	Std. Error	P value	OR	95% LCL	95% UCL
(Intercept)	0.27	0.25	0.28	1.30	0.81	2.11
pb(week)	-0.03	0.004	< 0.0001	0.97	0.96	0.98
symptom1	-1.17	0.46	0.011	0.31	0.13	0.76
sex1	-1.45	0.11	< 0.0001	0.24	0.19	0.29
age_grp2	-1.48	0.22	< 0.0001	0.23	0.15	0.35
age_grp3	-1.64	0.24	< 0.0001	0.19	0.12	0.31
outdoor1	-1.57	0.14	< 0.0001	0.21	0.16	0.27
public_transp1	1.10	0.13	< 0.0001	3.00	2.31	3.89
symptom1:sex1	1.93	0.16	< 0.0001	6.87	5.07	9.32
symptom1:age_grp2	2.80	0.45	< 0.0001	16.52	6.85	39.84
symptom1:age_grp3	2.30	0.46	< 0.0001	9.97	4.03	24.63
symptom1:outdoor1	2.70	0.18	< 0.0001	14.81	10.40	21.08

Table 19: Results of sensitivity analysis for winter testing by symptomatic status excluding those who participated less than 3 times

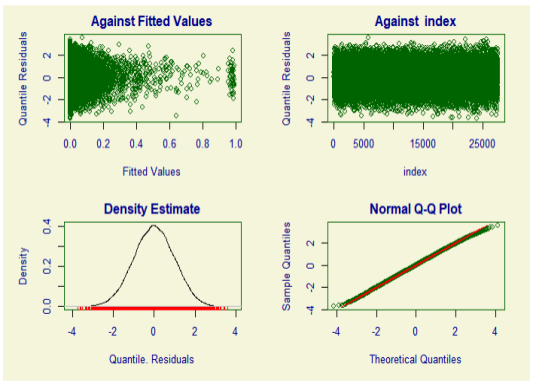
	Estimate	Std. Error	P value	OR	95% LCL	95% UCL
(Intercept)	-4.68	0.48	< 0.0001	0.01	0.00	0.02
pb(week)	-0.04	0.007	< 0.0001	0.96	0.95	0.97
symptom1	1.28	0.67	0.06	3.60	0.97	13.36
sex1	-0.53	0.21	0.01	0.59	0.39	0.88
age_grp2	-0.33	0.43	0.44	0.72	0.31	1.67
age_grp3	-1.02	0.46	0.03	0.36	0.15	0.89
outdoor1	0.001	0.25	0.997	1.00	0.61	1.64
public_transp1	0.17	0.22	0.44	1.19	0.77	1.84
symptom1:sex1	0.95	0.24	< 0.0001	2.59	1.61	4.17
symptom1:age_grp2	1.88	0.62	0.002	6.54	1.94	22.05
symptom1:age_grp3	2.56	0.65	< 0.0001	13.00	3.61	46.86
symptom1:outdoor1	0.67	0.29	0.022	1.95	1.10	3.45



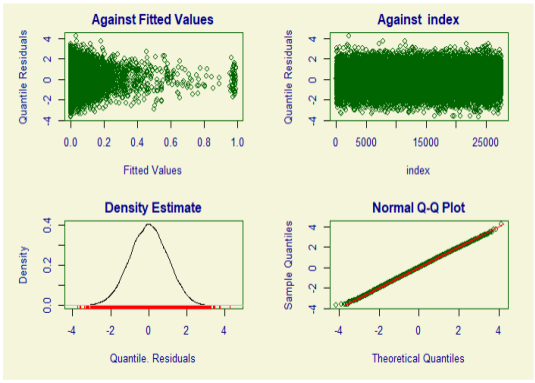
(a) Winter testing by vaccination status



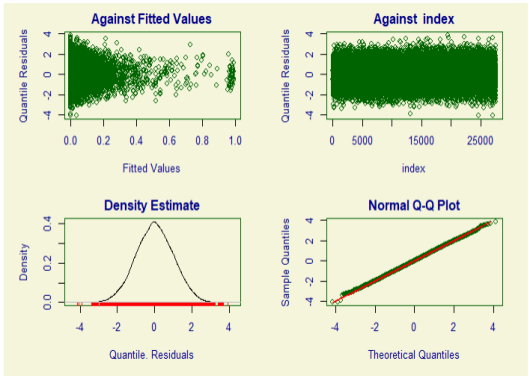
(b) Winter testing by symptomatic status



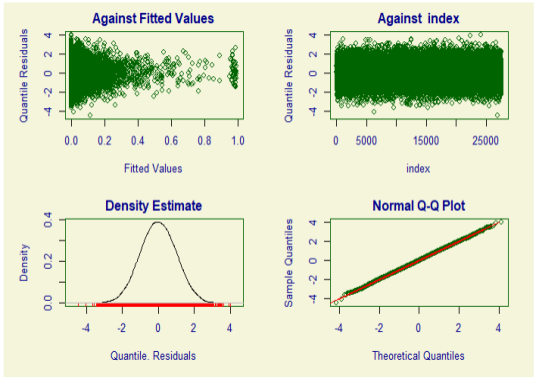
(c) Perceived severity



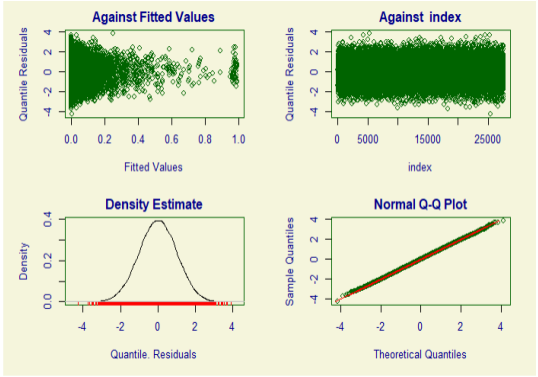
(d) Perceived susceptibility



(e) Perceived benefit to vulnerable

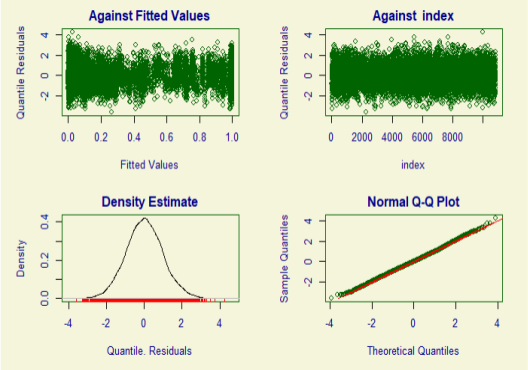


(f) Perceived long term impact

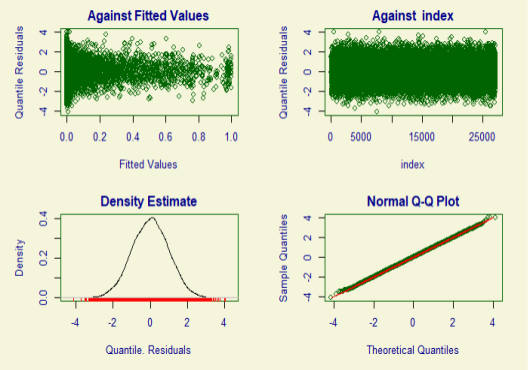


(g) Perceived benefit of vaccination

Figure 11: Model diagnostics for the GAMLSS models



(a) Sensitivity on testing



(b) Sensitivity on participation

Figure 12: Model diagnostics for sensitivity models