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COVID-19 vaccination attitudes across the European continent

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ABSTRACT

This study was conducted to determine the predictors of COVID-19 vaccination attitudes across multiple waves in seven countries geographically spread across the European continent, using data from a COVID-19 survey provided by the Massachusetts Institute of Technology COVID-19. Facebook users from across the globe participated in this survey which collected information on their knowledge of COVID-19, attitudes towards risk and available information, and their willingness or lack thereof to take the vaccine. In this secondary data analysis study, neural networks were used with special attention given to the importance of the predictors of COVID-19 vaccination attitudes. Perception of social norms regarding COVID-19 vaccination was found to be the most important predictor of vaccine acceptance. Country of residence and wave of data collection were among the important predictors, with different patterns for each country emerging across different waves. Other strong predictors included attitudes towards masks and mask wearing; attitudes towards the influenza vaccine; distrust in government health authorities and scientists; and level of knowledge of existing treatments for COVID-19. The results of this study can inform effective public health prevention and intervention efforts against infectious diseases.

1. Introduction

The COVID-19 pandemic became a major crisis event that has resulted in loss of life, health, livelihood, and mental wellbeing across all regions of the world. As of May 16, 2022, the number of confirmed COVID-19 cases stood at 521,395,017 and 6,288,845 deaths have been reportedi [1]. The first cases of the novel coronavirus were reported in China in late 2019 [2], and a few months later, in March 2020, the World Health Organization (WHO) issued an announcement characterizing the outbreak as a pandemic [3].

In Europe, the first case of COVID-19 was confirmed in France on January 24, 2020 [4]. Subsequently, Italy became the first European nation to experience a major outbreak of the novel coronavirus and the first country in the world to introduce a nationwide lockdown [5].

The COVID-19 pandemic is the first documented pandemic of coronavirus in human history [6] and has become the deadliest disease outbreak since the Spanish Flu of 1918–1919. The magnitude of the pandemic and its impact gave rise to an unprecedented, in scale and rapidity, race to develop a viable vaccine against the novel coronavirus. As of May 16, 2022, 35 vaccines have been approved in different countries and 672 vaccine trials are ongoing [7].

Despite the availability, substantial variations in COVID-19 vaccine acceptance rates have been reported across different countries. Moreover, such differences were observed in countries with similar levels of vaccine accessibility [8]. In a number of studies, these differences in attitudes towards COVID-19 vaccination were attributed to vaccine hesitancy [9,10].

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Vaccine hesitancy is defined as a "delay in acceptance or refusal of vaccination despite availability of vaccination services. Vaccine hesitancy is complex and context specific, varying across time, place and vaccines. It is influenced by factors such as complacency, convenience and confidence." [11] p4163]. Vaccine hesitancy has been recognized as a major threat to public health efforts aimed at containing and eradication of infectious diseases prior to the beginning of the COVID-19 pandemic [12]. Despite the fact that vaccination is one of the most powerful instruments of infectious disease control, perceptions of vaccines as unsafe and unnecessary have been gaining popularity for a number of years [13]. With the onset of the COVID-19 pandemic, research into the determinants of vaccine hesitancy has become one of the priority topics in public health.

In a recent review by Ref. [14], overall anti-vaccination stance, concerns about COVID-19 vaccine safety due to its rapid development, belief in the harmless nature of COVID-19, lack of trust in government, medical authority, and science, as well as doubts related to the efficiency and provenance of COVID-19 vaccines were identified as predictors of vaccine hesitancy.

In another review, focusing on high-income countries, the identified determinants of vaccine hesitancy included: demographic characteristics, such as younger age, female gender, and lower level of education; prior vaccination behaviours (no influenza vaccinations in pre-pandemic seasons); lower fear of COVID-19 and beliefs that it is not severe, as well as concerns related to safety and effectiveness of COVID-19 vaccines [15].

Despite the rapidly growing number of studies considering the determinants of vaccine hesitancy, further research is necessary to elucidate the contribution of different factors to vaccine hesitancy in the context of the COVID-19 pandemic.

1.1. The current study

The goal of the present study was to establish the determinants of vaccine hesitancy in the European region by fitting neural network models to a large-scale dataset obtained from a Facebook-based study conducted by researchers at the Massachusetts Institute of Technology (MIT).

Potential determinants included demographic variables related to knowledge and exposure to information of the respondent; and variables related to more general vaccination attitudes and beliefs regarding social norms held by the respondent. These are listed in more detail in the Method section. Neural networks are used to firstly obtain a list of characteristics which influence vaccine hesitancy in order of their importance and, secondly, they are used to classify the responses of individuals into the two categories: vaccine acceptance and vaccine hesitancy. Studies which made use of neural networks to investigate the factors that influence COVID-19 vaccine hesitancy include work by Refs. [16,17]:

[16] focused on adults from Portugal with data collection taking place between January and March 2021 and studied the effect of intentions, concerns and attitudes about the vaccine and COVID-19 on vaccine hesitancy.

Table 1
Categorical predictors according to vaccine attitude category.

Categorical Predictor	Vaccine Acceptance	Vaccine Hesitancy
Knowledge of existing treatments	I am unsure which is correct (5.8%) There is a drug to treat Covid-19 (4.4%) There is a vaccine for Covid-19 (41.3%) There is both a drug treatment and a vaccine for Covid-19 (8.4%) There is currently no drug treatment or vaccine for Covid-19 (40.1%)	I am unsure which is correct (13%) There is a drug to treat Covid-19 (6.3%) There is a vaccine for Covid-19 (24.8%) There is both a drug treatment and a vaccine for Covid-19 (6.2%) There is currently no drug treatment or vaccine for Covid-19 (49.6%)
Flu vaccine attitude	Yes (40.6%) No (54.6%) Don't know (4.8%)	Yes (11.6%) No (82.9%) Don't know (5.5%)
Infection severity	Not at all serious (7.3%) Somewhat serious (49.1%) Very serious (43.6%)	Not at all serious (20.5%) Somewhat serious (47.7%) Very serious (31.8%)
News source trust – Government health authorities	Do not trust (12.2%) Somewhat trust (44.6%) Trust (43.1%)	Do not trust (31.6%) Somewhat trust (46.9%) Trust (21.5%)
News source trust – Scientist	Do not trust (2.4%) Somewhat trust (24.1%) Trust (73.5%)	Do not trust (10.9%) Somewhat trust (43.9%) Trust (45.1%)
News source trust – Local health care workers	Do not trust (3.9%) Somewhat trust (37.3%) Trust (58.8%)	Do not trust (14.5%) Somewhat trust (49.4%) Trust (36.1%)
News medium trust – Television	Do not trust (11.7%) Somewhat trust (59.6%) Trust (28.7%)	Do not trust (31.2%) Somewhat trust (53.9%) Trust (14.9%)
News medium trust – Newspapers	Do not trust (15.7%) Somewhat trust (61.4%) Trust (22.8%)	Do not trust (32.4%) Somewhat trust (55.5%) Trust (12.0%)
News medium trust – Radio	Do not trust (10.0%) Somewhat trust (62.3%) Trust (27.7%)	Do not trust (27.1%) Somewhat trust (58.2%) Trust (14.7%)

Table 2
Mean and standard deviation of continuous variables and 5-point Likert-type items† by vaccine acceptance vs. hesitancy.

Variable	Mean (Standard Deviation)	
	Vaccine Acceptance	Vaccine Hesitancy
Social norms - vaccine	68.66 (21.703)	37.79 (25.527)
Social norms – physical distancing	60.3 (25.973)	50.54 (30.809)
Social norms – wearing face masks	78.64 (21.886)	72.19 (29.378)
Mask effectiveness†	4.16 (0.823)	3.46 (1.220)
Mask prevention†	4.77 (0.527)	4.44 (0.998)
Importance of physical distancing†	4.31 (0.790)	3.70 (1.182)
Importance of community action†	4.50 (0.682)	3.91 (1.138)
Community risk†	3.67 (0.911)	3.11 (1.100)

[17] conducted a U.S. based cross-sectional study between May 2020 and January 2021 which considered the influence of sociodemographic variables and variables related to perception of COVID-19 risk, the efficacy and necessity of the vaccine and preferred sources of information on COVID-19, on vaccine hesitancy. [18] provide a spatial map of vaccine attitudes in the U.S. based on a similar (but not identical) Facebook survey conducted between Carnegie Mellon University and University of Maryland.

The novel contribution of the present study is that it is a multinational study of both high- and medium-income economies, with the time period allocated for the data collection allowing our study and in particular, the classification made by the neural network, to be based on a much larger sample size and also to be analysed over a longer period of time.

2. Method

2.1. Data and sample

The data analysed in this study was obtained from the COVID-19 Preventive Health Survey conducted by researchers at the Massachusetts Institute of Technology (MIT) in partnership with Facebook. Facebook users from across the globe were invited to take part in an online survey with the aim of collecting information on their knowledge on COVID-19 and any risk factors involved, preventive measures taken, their willingness or lack thereof to take the vaccine and the sources used to keep abreast with news related to COVID-19. The MIT COVID-19 survey was administered 19 times during the period July 2020–March 2021 [19,20].

We shall refer to these multiple instances of data collection as 'waves'. For better manageability of the variable wave, each pair of waves was grouped into one wave, with the 19th wave being considered on its own. Thus, the wave variable considered in this analysis contained 10 levels in all.

In this paper we also analysed the way in which people's attitude towards the COVID-19 vaccine changes over time. Since this was a multinational study conducted on multiple waves, it was also possible to compare the said changes in attitude in different countries. Analysis in this paper was conducted on data collected from residents in countries with territory fully or partly in the European continent who completed the survey at multiple times at which the survey was administered between July 2020 and January 2021, resulting in a sample size of $n = 509{,}039$.

Due to a large number of missing values on multiple variables considered in the analysis, the main part of the analysis carried out using neural networks was conducted on smaller sample sizes (refer to Table 3 for sample sizes considered for models implemented). Each neural network model was fitted to a different sample size depending on the number of fully observed responses in terms of the variables used.

Table 3
Variables omitted for each model from previous model together with sample size.

Model	Variables Omitted From Previous Model (Normalized Variable Importance)	SampleSize
Model 1	N/A	14223
Model 2	News source trust – local health care workers (4.8%), News medium trust - newspapers (5.9%), Infection severity (8.3%))	14904
Model 3	News medium trust - television (10.1%), News medium trust - radio (13.7%),	15689
Model 4	Importance of community action (16.8%)	15810
Model 5	Importance of physical distancing (16.5%), Community risk (17.5%), Social norms on wearing face masks (21.4%)	64523
Model 6	Mask prevention (22.6%), News source trust - scientists (26.7%), News source trust – government health authorities (27.3%), Knowledge of existing treatments (28.3%),	192391

2.2. Measures

Since the main aim of the study was to establish the predictors of vaccine hesitancy, variables included in the analysis were as follows: i) demographic characteristics: gender, age group, the highest level of completed education, the density of the respondent's living area, country of residence, self-reported state of health and employment related questions; ii) information exposure to content related to coronavirus; iii) knowledge about the disease itself and knowledge of persons who tested positive for the disease; iv) vaccine and healthcare related questions with a question specifically asking the respondent to state whether they plan to take the vaccine if it becomes available; v) sources from which information was acquired during the week before the survey was carried out and whether such sources were to be trusted; vi) knowledge about groups who are more at risk of getting the disease; vii) distancing measures and perceived norms; viii) risk perceptions; ix) preventive behaviours and measures taken; x) locations that will be visited in the two weeks following the filling in of the survey, and xi) future actions in terms of mask wearing and taking the vaccine if made available. Specific questions used in the MIT survey to assess these variables can be found in the Appendix. In addition, the wave variable was also taken into consideration.

2.3. Statistical analysis

Descriptive statistical analysis, hypothesis testing and model fitting were performed using IBM SPSS version 27, particularly due to the speed at which it manages to fit a neural network model. The outcome variable of interest was *vaccine acceptance*. This was a dichotomous variable with two categories: acceptance and hesitancy. In the original questionnaire, respondents were asked whether they were willing to take the vaccine or had taken it. Those respondents who had already received the vaccine and those who planned to take the vaccine when it became available were classified as demonstrating vaccine acceptance. Those who were not taking the vaccine and those who were sceptical about the vaccine or were unwilling to take it were classified as demonstrating vaccine hesitancy.

Descriptive statistics were first obtained on vaccine attitude and also on the measures which were considered to be potential predictors of vaccine hesitancy. This was followed by testing for significance using the Pearson chi-square test of independence for categorical (ordinal or nominal) predictors and the independent samples *t*-test for continuous predictors. Due to the large number of nominal variables in the data set (119 in total, including country and wave), Cramer V was used to measure effect size for the Pearson chi-square test for categorical variables. It was decided to include country and wave in the model due to our interest in country and wave differences. All the other categorical variables resulted to be significant with a p-value <0.001. It was decided to only include those categorical variables with corresponding Cramer V value greater than 0.2. The categorical predictors included are the following, in order of Cramer V value shown in the brackets: mask effectiveness (0.3228), news source trust - scientists (0.3017), importance of community action (0.2982), news source trust – government health authorities (0.2975), importance of physical distancing (0.2974), community risk (0.2661), news source trust – local health care workers (0.2582), news medium trust - radio (0.2468), news medium trust - newspapers (0.2155), news medium trust - television (0.2155), mask prevention (0.2112), infection severity (0.2059), knowledge of existing treatments (0.2055).

Only three continuous variables were present in data, and these were all included as they rejected the null hypothesis of no difference in the independent samples *t*-test. These were: a) social norms – vaccines; b) social norms – wearing face masks; c) social norms – physical distancing.

The final part of the analysis involved the fitting of multiple artificial neural networks (ANNs) using only the variables which were found to significantly influence vaccine hesitancy. Artificial Neural Networks (ANNs) have been applied in a wide range of applications aimed at either predicting or classifying responses of a variable of interest. In this paper, neural networks were used to firstly obtain a list of variables which influence vaccine hesitancy in order of their importance and secondly, the predicted responses were compared to the actual responses. Based on the final classification of respondents, we were able to discuss the overall classification performance of the neural network.

A single layer feedforward ANN, which is the model used in this study, is a collection of nodes organised in a number of layers as shown in Fig. 1. Each node in the input layer represents one of the measures being considered. These measures can be both qualitative and quantitative. The number of nodes in the hidden layer is chosen automatically by the software to provide the best accuracy. The output layer contains as many nodes as there are levels in the qualitative variable used for classification. In this case, respondents have to be classified into either "vaccine acceptance" or "vaccine hesitancy", leading to two nodes in the output layer.

The connections between the nodes in the different layers are sometimes called edges and typically have weights associated with them. A large weight signifies a strong link between two connected neurons. The output layer is modelled by some non-linear function involving the sum of the neurons in the input layer.

We denote the nodes in the input layer by x_i, where $i = 0, 1, \ldots P$. Here P denotes the number of variables in the data set and x_0 denotes the so-called bias term. This term appears in the input and hidden layers of a neural network. Each node z_j, for $j = 0, 1, \ldots C$ in the hidden layer can be represented as a weighted sum of the nodes in the input layer:

$$z_j = h^H \sum_{j=0}^{P} w_{ij}^{(1)} x_i$$

Note: $C + 1$ denotes the number of neurons in the hidden layer. Usually, z_0 is the so-called bias term. The term h^H is the so-called activation function at the hidden layer and $w_{ij}^{(1)}$ represents the weights of the hidden layer. In IBM SPSS version 27 the activation function in the hidden layer is taken to be the hyperbolic tangent. Finally, the nodes in the output layer, which we denote by y_k for $k =$

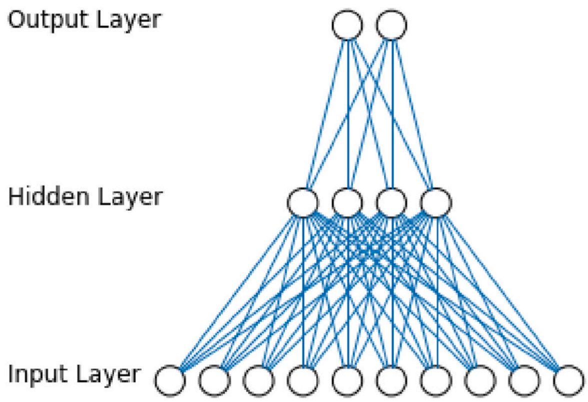

Fig. 1. The single layer feedforward neural network. The input layer represents the x_i s, the hidden layer the z_j s, and the output layer the y_k.

$1, 2$, can be written as follows:

$$y_k = h^0 \sum_{j=0}^{C} w_{jk}^{(2)} z_j$$

where h^0 is the activation function at the output layer and $w_{jk}^{(2)}$ represents the weights of the output layer. Hence, combining the above two equations we get:

$$y_k = h^0 \left(\sum_{j=0}^{C} w_{jk}^{(2)} h^H \left(\sum_{j=0}^{P} w_{ij}^{(1)} x_i \right) \right)$$

In IBM SPSS, the activation function of the output layer is taken to be the *softmax* function. This activation function is used as it outputs numbers between 0 and 1, which in our application, are considered to be the probability that an individual is classified in each of the two classes. To find the optimal weights, the Scaled Conjugate Gradient method was used. SPSS allows the user to choose between the Gradient descent algorithm and the Scaled Conjugate Gradient (SCG) algorithm. The former is well known in optimization theory and is characterised by a poor convergence rate within the context of Neural Networks. Moreover, it depends on a number of user-specified parameters [21]. devised the so-called scaled conjugate gradient algorithm to tackle the problems in the Gradient descent algorithm. The author argued that in realistic applications of Neural Networks the computations required are rather heavy and hence only optimization methods that can be applied to large-scale problems should be used. In the numerical analysis community, the family of such algorithms are generally referred to as the Conjugate Gradient Methods. The SCG avoids using line-search algorithms in each learning iteration and instead applies the Levenberg-Marquardt approach to improve performance. A number of authors including [22] argued that SCG does indeed perform better than Gradient descent. Hence, in this study we decided to apply the SCG algorithm when fitting a Neural Network to that data set.

3. Results

The presentation of results in this section is divided into three parts. The first part involves descriptive statistics for several predictor variables by vaccine attitude categorisation. The second part considers the plots of two variables – country and knowledge of existing treatments – by wave and vaccine attitude categorisation to appreciate the time dependency of these variables. Finally, we conclude with the modelling aspect using artificial neural networks with model selection via variable importance.

3.1. Descriptive statistics for predictor variables

We now look at the descriptive statistics tables of the variables included in the neural network model (Table 1 and Table 2) related to the vaccine attitude categorisation (acceptance/hesitancy). Detailed descriptions of the predictors included in the model can be found in the Appendix. We are not including information on three variables – country, wave and knowledge of existing treatments—in this section, as the time-varying nature in these three variables was of particular interest and shall be discussed in the second part of this section.

From the visual inspection of Table 1, a number of preliminary observations can be made. Respondents in the vaccine acceptance category were more likely to take the flu vaccine in previous seasons than the respondents in the vaccine hesitancy category. They were also more likely to consider COVID-19 to be a severe illness than the respondents in the vaccine hesitancy category. Respondents in the vaccine acceptance category appeared to show more trust in news from government health authorities, scientists, and local health care workers in comparison to the respondents in the vaccine hesitancy category. However, it must also be noted that trust in government health authorities was consistently lower than trust in scientists and local health care workers across all groups.

None of the news media (television, newspaper, radio) gained the majority of full trust in either of the two categories. Distrust and lack of full trust was particularly prevalent in the respondents' attitude towards newspapers. Respondents categorised as vaccine hesitant demonstrated stronger distrust across all types of news media.

Respondents in the vaccine acceptance group were observed to be more in favour of mask wearing, social distancing, and community action to prevent the spread than the individuals in the vaccine hesitancy group. Moreover, respondents in the vaccine acceptance category were more likely to consider COVID-19 to be a risk to the community, more so than the respondents in the vaccine hesitancy group.

Respondents in the vaccine acceptance category appeared to know more people who were planning to take the vaccine, wore mask/ face covering, and maintained social distancing, than the respondents in the vaccine hesitancy category.

As can be seen in Table 2, respondents in the vaccine acceptance category demonstrated higher scores on perceived social norms regarding COVID-19 vaccination (i.e. they were more likely to believe that people in their social circle would agree to get vaccinated). The gap between the two means is smaller when considering perceived social norms for physical distancing and perceived social norms for wearing face masks; however, the mean remains higher in the vaccine acceptance category. Furthermore, for the Likert type variables (mask effectiveness, mask prevention, importance of physical distancing, importance of community action, community risk), the means in the vaccine acceptance category are also consistently higher.

3.2. COVID-19 vaccination attitude change over time

Attitudes towards vaccination changed with each wave for different countries, represented by the two categories of the dichotomous variable *vaccine attitude* – acceptance and hesitancy.

3.3. Country and wave

In Fig. 2 it can be observed that the study participants in different countries had different attitudes regarding COVID-19 vaccination. In the UK and Italy, the overall acceptance proportions were always higher than the hesitancy proportions; however, this was not the case for Poland, Romania and France, where the majority of respondents were hesitant over multiple waves, particularly the early ones. Furthermore, for waves 3–6 in Germany and 4–7 in Turkey, acceptance/hesitancy proportions were divided almost equally. A positive change in attitude towards vaccines can also be noted from wave 6 onwards in the UK, wave 8 onwards in Turkey, and wave 7 onwards in the remaining (European Union) countries. This change in attitude corresponds to the commencement of the vaccine rollouts in these countries, with the UK having the earliest vaccine rollout early in December, European Union countries starting their vaccine rollout towards the end of December, and Turkey starting in mid-January.

3.4. Knowledge of existing treatments

The question regarding the knowledge of existing treatment also had a strong relationship with the wave. The question had the following possible responses: "I am unsure which is correct"; "There is a drug to treat COVID-19"; "There is a vaccine for COVID-19"; "There is both a drug and a vaccine for COVID-10", and "There is currently no drug and no vaccine for COVID-19".

In Fig. 3, it can be seen that, in particular, the percentage of responses for "There is a vaccine for COVID-19" and "There is currently no drug and no vaccine for COVID-19" changed with time, the former being the predominant response in the later waves, and the latter being the predominant response in the initial waves. This, of course, comes as no surprise as the former response was the correct answer towards the later waves and the latter response was the correct answer for the initial waves. However, from the plot it is observed that the correct answer was always more predominant for the vaccine acceptance group than for the vaccine hesitancy group. The reply for "There is both a drug and a vaccine for COVID-19" also increased with time – while this was not the correct answer, as at the time of the study, there was no officially approved drug against COVID-19, there were reports of drugs which were being used by professionals to alleviate the symptoms and improve chances of survival which may have prompted respondents to give this answer.

3.5. Neural networks

A total of six neural network models were fitted on the data set, each model having less variables than its predecessor. In Table 3, Model 1 is shown to be the full model with all variables included, while for Model 2 to 6 we present the omitted variables together with their normalized importance from the previous model. The corresponding valid sample size for each model is also given. It can be seen that as less important variables started being removed, the sample size steadily increased. To test accuracy of each model, a 70:30 ratio for the test and the training set is taken. From the initial Model 1, variables with less than 10% normalized importance were discarded and Model 2 was fit. The variables with less than 15% normalized importance were discarded and the rest were used to create Model 3. The procedure was repeated five times, with the percentage of normalized importance increased by 5% at each step, until a significant decrease in accuracy was detected.

Fig. 4 illustrates the values of the accuracy and the area under the curve achieved in each of the six neural network models. The accuracy is defined as the ratio of the correctly classified observations over the total number of observations. The area under the curve (AUC) measures the area under the so-called Receiver Operator Characteristic (ROC) curve. The ROC curve shows the classification

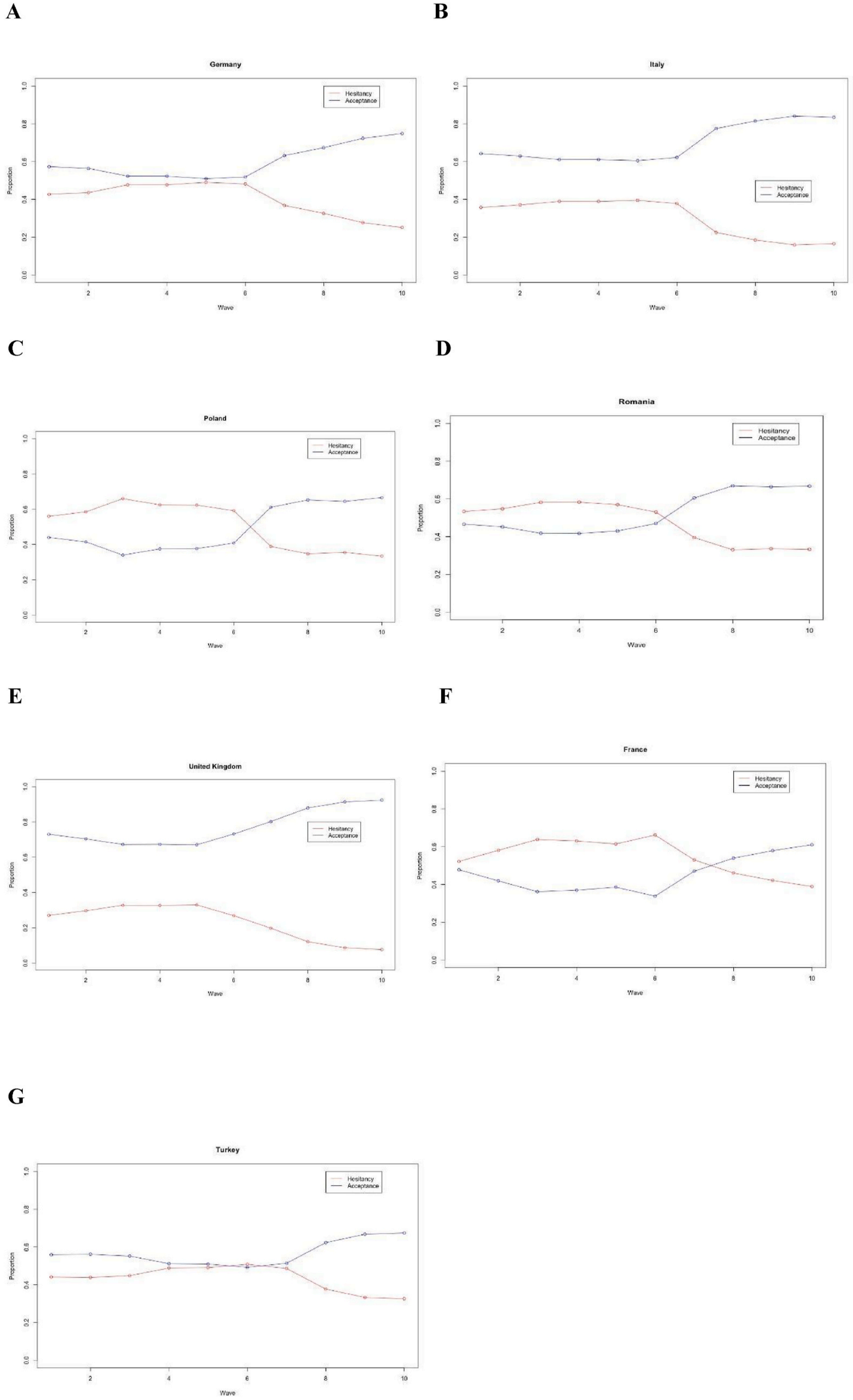

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Fig. 2. Plots of vaccine acceptance (blue) and vaccine hesitancy (red) proportions by country and wave.

performance for all possible probability cut-offs in a plot of sensitivity versus specificity values. Any classification model should have an AUC higher than 0.5 and the closer the area is to 1 the better the predictive power of the neural network. To obtain the accuracy and the AUC measures, each neural network model was applied on the respective testing set.

It can be observed that there was a slow decrease in both accuracy and AUC until Model 5, followed by a sheer drop in both performance measures in Model 6. This led to the decision to choose Model 5 as this gave the best trade-off between model complexity (i.e. the number of variables used) and the quality of the results. Model 5 contained 10 nodes in the hidden layer. We next discuss the results of Model 5. To evaluate the fit of the chosen neural network model, the classification results shown in Table 4 were obtained.

In Table 4, we can see that for both the training and the testing set, the neural network model was extremely successful in correctly predicting the respondents in the acceptance groups (90% and 89.2%). The percentage of correct predictions for the hesitant groups were slightly lower at 62.1% and 62.3%, possibly due to a more complex decision-making process involved in choosing to not take the COVID-19 vaccine. One main drawback is that it contained a lot of incomplete survey responses and the sample size used to fit this neural network was of 64523 with a training set of 45095 (70%) individuals, and a testing set of 19428 (30%) individuals, thus excluding 444516 individuals from the original sample size. This great reduction is due to the variables whose full set of responses was not available for the variables considered. An overall percentage of correct predictions at around 80% for both groups and an AUC of 0.867 however show that the fitted neural network still managed to achieve high prediction capability, despite the reduced sample size. It can also be observed that the accuracy for the training and testing samples are very similar, with the overall percentage for the former being 80.8% and for the latter being 80.3%. This shows that the neural network model is not over-fitted. This is also corroborated by the fact that the percentage of correctly classified individuals in the acceptance groups for the training and testing samples are almost identical (72.9% and 72.1%). The same can be said for the percentages achieved for the hesitancy groups (27.1% and 27.9%).

The variables which had the highest impact in classifying vaccine hesitancy for Model 5 are presented in Table 5 in order of their importance and normalized importance. Table 5 shows that *social norms - vaccine* had the greatest importance on the predictive ability of the neural network, with an importance of 0.261 and a normalized importance of 100% showing that social norms greatly influence the attitudes towards vaccine. This was followed by mask effectiveness with a normalized importance (53.7%), though the normalized importance of this variable is slightly more than half that of the most important one. Noting that the variables mask effectiveness, mask

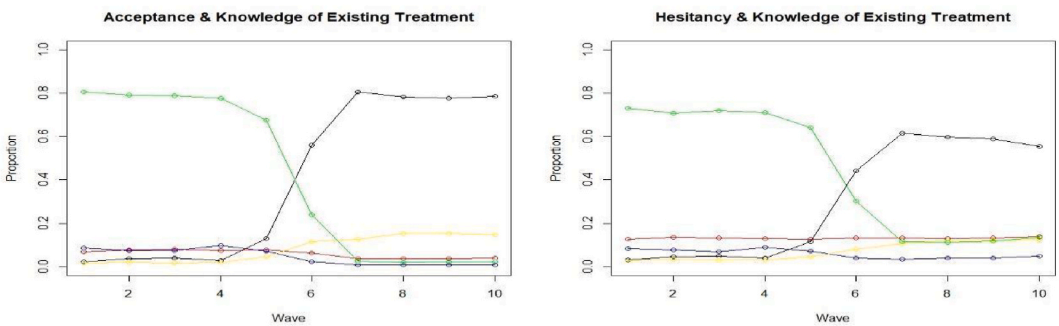

Fig. 3. Plots of different response proportions across wave for both the vaccine acceptance group (left) and vaccine rejection group (right) – "I am unsure which is correct" (red), "There is a drug to treat COVID-19" (blue), "There is a vaccine for COVID-19" (black), "There is both a drug and a vaccine for COVID-10" (yellow) and "There is currently no drug and no vaccine for COVID-19" (green).

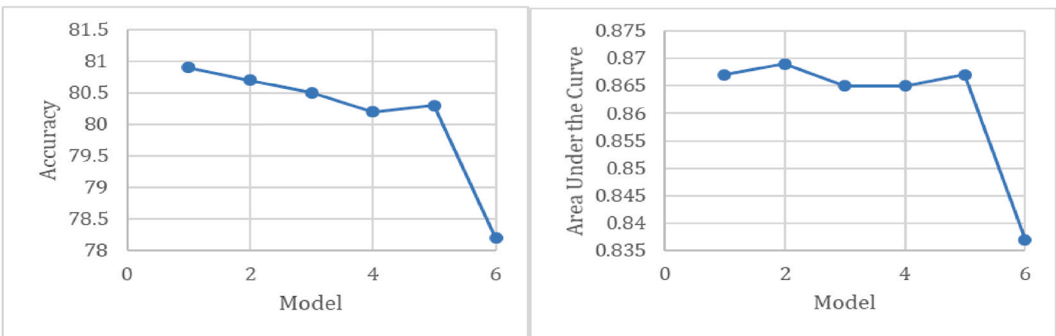

Fig. 4. Accuracy and area under the curve from model 1 to model 6.

Table 4
Classification table for both training and test set.

Classification				
Sample	Observed	Predicted		
		Acceptance	Hesitancy	Percent Correct
Training	Acceptance	27231	3021	90.0%
	Hesitancy	5629	9214	62.1%
	Overall Percent	72.9%	27.1%	80.8%
Testing	Acceptance	11584	1404	89.2%
	Hesitancy	2428	4012	62.3%
	Overall Percent	72.1%	27.9%	80.3%

Table 5
Variable importance and normalized variable importance of variables included in Model 5.

	Importance	Normalized Importance
Social norms – vaccine	0.261	100.00%
Mask effectiveness	0.14	53.70%
Flu vaccine attitude	0.108	41.50%
Country	0.087	33.40%
Wave	0.076	29.10%
Knowledge of existing treatments	0.074	28.30%
News source trust – government health authorities	0.071	27.30%
News source trust – Scientists	0.07	26.70%
Mask Prevention	0.059	22.60%
Social norms – wearing a face mask	0.056	21.40%

prevention and social norms – wearing a face mask all made it to the list of most important variables, this indicates that attitudes related to mask wearing are good predictors of one's attitude towards the vaccine. As expected, flu vaccine attitude also turned out to be an important variable, as was the response to knowledge of existing treatments, news source trust – government health authorities and news source trust - scientists. As expected, country and wave were also important when it came to vaccine attitudes, ranking towards the middle of the table.

4. Discussion

The goal of this secondary data analysis was to utilize a neural networks approach to establish the predictors of COVID-19 vaccination acceptance in the European region. Perceived social norms in relation to COVID-19 related restrictions and vaccines, history of accepting flu vaccinations in previous seasons, attitudes towards mask wearing, and distrust of the media were found to be the important predictors of vaccine acceptance vs. vaccine hesitancy. In addition, country-to-country differences in COVID-19 vaccination acceptance were noted, with France, Poland and Romania being the most hesitant, and UK and Italy being the most accepting. High vaccine hesitancy in Poland is reported in Ref. [23], which documents that in a survey of 13426 people in 19 countries, Poland has the highest proportion of negative responses towards COVID-19 vaccine acceptance. High vaccine hesitancy in France, on the other hand, is also mentioned in Ref. [24] where it is quoted that, in December 2020, willingness to get vaccinated in France amounted to 40%.

This study also determines that time was a contributing factor in the attitude change towards COVID-19 vaccination, with the respondents in later waves becoming more receptive to vaccines.

The just mentioned predictors have contributed to detecting accurately the two categories (vaccine acceptance and vaccine hesitancy) with an accuracy of 80.3%, though it was found that neural networks are much more likely to correctly detect the vaccine acceptance category (89.2% accuracy) than they are to detect the vaccine hesitancy category (62.3% accuracy). This is an indication that vaccine hesitancy respondents may constitute a more diverse group, with some being mildly sceptical and others being strongly against, and also potentially having different reasons for being hesitant. Information on seasonal influenza vaccine uptake was one of the important predictors for COVID-19 vaccine attitudes. In Ref. [25] high seasonal influenza vaccine confidence was found in the UK (83.2%) while relatively low seasonal influenza vaccine confidence was found in France (71.5%), which is indicative of the respective high and low confidence in COVID-19 vaccines in this study for the two countries. However, this predictor was not capable of predicting COVID-19 hesitancy perfectly, which shows that attitudes for the two vaccines varies. Further research is necessary to determine the characteristics of individuals demonstrating COVID-19 vaccine hesitancy.

The findings in this study corroborate the results reported by other authors [14]. identified belief in the harmless nature of COVID-19 and lack of trust in governments, medical authority and science as important predictors. This distrust is also evident from our study, and we have also shown that belief in the harmless nature of COVID-19 for people in the vaccine hesitancy group is particularly evident in attitudes people in this group have towards mask wearing. On the other hand [15], determined that lower fear of COVID-19 and beliefs that it is not severe is an important predictor, but also mentioned prior vaccination behaviours. This corroborates our findings regarding attitudes to influenza vaccination as a strong predictor of current COVID-19 vaccination attitudes. Finally, perceived social norms (perceptions of other people's typical behaviours and attitudes, distinct from actual norms) have long been associated with a variety of health-related behaviours [26–28]. Our findings in this study agree with the results of other research studies that have considered the role of perceived social norms in the context of the COVID-19 vaccination behaviours. For instance Refs. [29,30], in separate samples of U.S. college students, found that perceived social norms (in both, perception of vaccine uptake rate in one's peer/social group) acted as a significant predictor of vaccine hesitancy [31]. demonstrate that herding and perceived social norms (conceptualised as the social pressures of getting vaccinated) are positively correlated with vaccine uptake, while [32] conduct a multi-country study to demonstrate that perceived social norms (conceptualised as respondents' belief that most of their close family and friends would get a COVID-19 vaccine) were among the strongest correlates of vaccine acceptance in four out of six country samples. Furthermore [33], assessed perceived social norms (likelihood of family and friends engaging in a particular behaviour) for 18 preventive behaviours, including physical distancing and mask wearing, in a national survey of UK population. The results of this study showed that significant increases in the odds of performing 11 preventive behaviours was predicted by each unit increase in perceived social norms among friends and family, including 66% greater odds of mask wearing. Finally [34], find that an individual's perceived strength of social norms such as mask wearing and social distancing is negatively correlated to the level of COVID-19 risk perception and positively correlated with beneficial psychological outcomes.

Studies on the determinants of COVID-19 vaccine hesitancy are important, as the threat of emerging diseases and future pandemics remains high. Knowing which factors influence a person's decision to accept vaccination or not is important for policy makers and health authorities tasked with developing proactive and effective public health interventions. Moreover, it is important to address misinformation and other factors that may negatively impact trust in health authorities on behalf of individuals and communities.

Author contribution statement

Fiona Sammut, David Suda, Mark Anthony Caruana: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Olga Bogolyubova: Conceived and designed the experiments; Performed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Data availability statement

This research is based on survey results from the Massachusetts Institute of Technology. As per clause 2.6 in MIT Facebook Research Data Use Agreement, only aggregate results can be published. For more information, please refer to the website (https://dataforgood.facebook.com/dfg/tools/covid-19-preventative-health-survey).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Variable Name (Short)	Variable Meaning
wave	Wave
country	Country
vaccine attitude	vaccine attitude
flu vaccine attitude	Have you taken the flu vaccine this fall or do you plan to take one in the coming weeks?
mask effectiveness	How effective is wearing a face mask for preventing the spread of Covid-19?
knowledge of existing treatments	Knowledge of existing treatments – which of the following is correct?
mask prevention	How often are you able to wear a mask or face covering when you are in public?
importance of physical distancing	How important do you think physical distance is for slowing the spread of Covid-19?
importance of community action	How important is it for you to take actions to prevent the spread of Covid-19 in your community?
community risk	How dangerous do you think the Covid-19 risk is to your community?
infection severity	How serious would it be if you became infected with Covid-19?
social norms – vaccines	Out of 100 people in your community, how many do you think would take a Covid-19 vaccine if it were made available?
social norms – physical distancing	Out of 100 people in your community, how many do you think maintain a distance of at least 1 m from others?
social norms – wearing face masks	Out of 100 people in your community, how many do you think would wear a face mask or covering?

(continued on next page)

(*continued*)

Variable Name (Short)	Variable Meaning
news source trust – government health authorities	How much do you trust government health authorities as a news source?
news source trust – scientists	How much do you trust scientists as a news source?
news source trust – local health care workers	How much do you trust local health workers as a news source?
news medium – television	How much do you trust television as a news medium?
news medium – newspapers	How much do you trust newspapers as a news medium?
news medium – radio	How much do you trust radio as a news medium?

References

[1] Retrieved from, Worldometer – COVID-19 Coronavirus Pandemic, 2022, https://www.worldometers.info/coronavirus/.
[2] Centers for Disease Control and Prevention, CDC Museum COVID-19 Timeline, Retrieved from, 2022, https://www.cdc.gov/museum/timeline/covid19.html.
[3] Retrieved from, WHO Director-General's opening remarks at the media briefing on COVID19 -March 2020, 2020, https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19—11-march-2020.
[4] Licence: CC BY-NC-SA 3.0 IGO, A Timeline of WHO's Response to COVID-19 in the WHO European Region: a Living Document (Version 2.0 from 31 December 2019 to 31 December 2020), WHO Regional Office for Europe, Copenhagen, 2021.
[5] A. Saglietto, F. D'Ascenzo, G.B. Zoccai, G.M. De Ferrari, COVID-19 in Europe: the Italian lesson, Lancet 395 (10230) (2020) 1110–1111, https://doi.org/10.1016/S0140-6736(20)30690-5.
[6] Y.C. Liu, R.L. Kuo, S.R. Shih, COVID-19: the first documented coronavirus pandemic in history, Biomed. J. 43 (4) (2020) 328–333, https://doi.org/10.1016/j.bj.2020.04.007.
[7] Retrieved from, COVID-19 Vaccine Tracker, 2022, https://covid19.trackvaccines.org/.
[8] M. Sallam, M. Al-Sanafi, M. Sallam, A global map of COVID-19 vaccine acceptance rates per country: an updated concise narrative review, J. Multidiscip. Healthc. 15 (November 2021) (2022) 21–45, https://doi.org/10.2147/JMDH.S347669.
[9] M. Sallam, Covid-19 vaccine hesitancy worldwide: a concise systematic review of vaccine acceptance rates, Vaccines 9 (2) (2021) 1–15, https://doi.org/10.3390/vaccines9020160.
[10] M.G. Salomoni, Z. Di Valerio, E. Gabrielli, M. Montalti, D. Tedesco, F. Guaraldi, D. Gori, Hesitant or not hesitant? A systematic review on global covid-19 vaccine acceptance in different populations, Vaccines 9 (8) (2021) 1–26, https://doi.org/10.3390/vaccines9080873.
[11] N.E. MacDonald, J. Eskola, X. Liang, M. Chaudhuri, E. Dube, B. Gellin, S. Goldstein, H. Larson, M.L. Manzo, A. Reingold, K. Tshering, Y. Zhou, P. Duclos, S. Guirguis, B. Hickler, M. Schuster, Vaccine hesitancy: definition, scope and determinants, Vaccine 33 (34) (2015) 4161–4164, https://doi.org/10.1016/j.vaccine.2015.04.036.
[12] Retrieved from, Ten Threats to Health in 2019, 2019, https://www.who.int/news-room/spotlight/ten-threats-to-global-health-in-2019.
[13] E. Dubé, C. Laberge, M. Guay, P. Bramadat, R. Roy, J. Bettinger, Vaccine hesitancy: an overview, Hum. Vaccines Immunother. 9 (8) (2013) 1763–1773.
[14] G. Troiano, A. Nardi, Vaccine hesitancy in the era of COVID-19, Publ. Health 194 (2021) 245–251, https://doi.org/10.1016/j.puhe.2021.02.025.
[15] J. Aw, J. Jie, B. Seng, S. Si, Y. Seah, L.L. Low, COVID-19 vaccine hesitancy — a scoping review of literature in high-income countries, Vaccines 9 (8) (2021) 900, https://doi.org/10.3390/vaccines9080900.
[16] N. Fernandes, D. Costa, D. Costa, J. Keating, J. Arantes, Predicting covid-19 vaccination intention: the determinants of vaccine hesitancy, Vaccines 9 (10) (2021), https://doi.org/10.3390/vaccines9101161.
[17] P. Mondal, A. Sinharoy, L. Su, Sociodemographic predictors of COVID-19 vaccine acceptance: a nationwide US-based survey study, Publ. Health 198 (June) (2021) 252–259, https://doi.org/10.1016/j.puhe.2021.07.028.
[18] H.J. Larson, E. Gakidou, C.J.L. Murray, The vaccine-hesitant moment, N. Engl. J. Med. 387 (1) (2022) 58–65, https://doi.org/10.1056/NEJMra2106441.
[19] A. Collis, K. Garimella, A. Moehring, M.A. Rahimian, S. Babalola, N.H. Gobat, D. Shattuck, J. Stolow, S. Aral, D. Eckles, Global survey on COVID-19 beliefs, behaviours and norms, Nat. Human Behav. (2022), https://doi.org/10.1038/s41562-022-01347-1.
[20] Retrieved from, MIT COVID-19 Beliefs, Behaviors and Norms Survey, 2020, https://covidsurvey.mit.edu/dashboard.html.
[21] M.F. Moller, A scaled conjugate gradient algorithm for fast supervised learning, Neural Network. 6 (4) (1993) 525–533, https://doi.org/10.1016/S0893-6080(05)80056-5.
[22] Z. Lin, J. Maris, L. Hermans, J. Vandewalle, Z. Chen, Comparison of gradient descent and conjugate gradient learning algorithms for classification of electrogastrogram, 17(1), in: Proceedings of the 1995 IEEE Engineering in Medicine and Biology 17th Annual Conference and 21st Canadian Medical and Biological Engineering Conference, 1995, pp. 817–818.
[23] J.V. Lazarus, S.C. Ratzan, A. Palayew, L.O. Gostin, H.J. Larson, K. Rabin, S. Kimball, A. El-Mohandes, A global survey of potential acceptance of a COVID-19 vaccine, Nat. Med. 27 (2) (2021) 225–228, https://doi.org/10.1038/s41591-020-1124-9.
[24] L. Cambon, M. Schwarzinger, F. Alla, Increasing acceptance of a vaccination program for coronavirus disease 2019 in France: a challenge for one of the world's most vaccine-hesitant countries, Vaccine 40 (2) (2022) 178–182, https://doi.org/10.1016/j.vaccine.2021.11.023.
[25] A. De Figueiredo, E. Karafillakis, H.J. Larson, State Of Vaccine Confidence In The EU+UK. A Report For The European Commission, Retrieved from, 2020, https://health.ec.europa.eu/vaccination/state-vaccine-confidence_en.
[26] J.H. Kunz, R.N. Greenley, K.A. Mussatto, B. Roth-Wojcicki, T. Miller, M.E. Freeman, S. Lerand, Personal attitudes, perceived social norms, and health-risk behavior among female adolescents with chronic medical conditions, J. Health Psychol. 19 (7) (2014) 877–886, https://doi.org/10.1177/1359105313481077.
[27] E. Robinson, Perceived social norms and eating behaviors: an evaluation of studies and future directions, Physiol. Behav. (152) (2015) 397–401, https://doi.org/10.1016/j.physbeh.2015.06.010.
[28] J. Strough, E.R. Stone, A.M. Parker, W. Bruine de Bruin, Perceived social norms guide health care decisions for oneself and others: a cross-sectional experiment in a US online panel, Med. Decis. Making 42 (3) (2022) 326–340, https://doi.org/10.1177/0272989X211067223.
[29] S. Graupensperger, D.A. Abdallah, C.M. Lee, Social norms and vaccine uptake: college students' COVID vaccination intentions, attitudes, and estimated peer norms and comparisons with influenza vaccine, Vaccine 39 (15) (2021) 2060–2067, https://doi.org/10.1016/j.vaccine.2021.03.018. Epub.2021.Mar.17. PMID: 33741191; PMCID: PMC7965606.
[30] A.E. Jaffe, S. Graupensperger, J.A. Blayney, J.C. Duckworth, C.A. Stappenbeck, The role of perceived social norms in college student vaccine hesitancy: implications for COVID-19 prevention strategies, Vaccine 40 (12) (2022) 1888–1895, https://doi.org/10.1016/j.vaccine.2022.01.038.

[31] M. Agranov, M. Elliott, P. Ortoleva, The importance of social norms against strategic effects: the case of covid-19 vaccine uptake, Econ. Lett. 206 (2021), 109979, https://doi.org/10.1016/j.econlet.2021.109979.Epub.2021.Jul.2. PMID: 34230727; PMCID: PMC8252706.
[32] T.P. Davis Jr., A.K. Yimam, M.A. Kalam, A.D. Tolossa, R. Kanwagi, S. Bauler, L. Kulathungam, H. Larson, Behavioural determinants of COVID-19-vaccine acceptance in rural areas of six lower- and middle-income countries, Vaccines 10 (2) (2022) 214, https://doi.org/10.3390/vaccines10020214.
[33] M.H. Goldberg, A. Gustafson, E.W. Maibach, S. van der Linden, M.T. Ballew, P. Bergquist, J.E. Kotcher, J.R. Marlon, S.A. Rosenthal, A. Leiserowitz, Social Norms Motivate COVID-19 Preventive Behaviors, PsyArXiv, 2020, https://doi.org/10.31234/osf.io/9whp4.
[34] S. Liu, J. Zhu, Y. Liu, D. Wilbanks, J.C. Jackson, Y. Mu, Perception of strong social norms during the COVID-19 pandemic is linked to positive psychological outcomes, BMC Publ. Health 22 (2022) 1403, https://doi.org/10.1186/s12889-022-13744-2.