How to Improve Compliance with Protective Health Measures During the Covid-19 Outbreak: Testing a Moderated Mediation Model and Machine Learning Algorithms

Cristina Mazza, Merylin Monaro, Laura Muzi, Marco Colasanti, Eleonora Ricci, Silvia Biondi, Stefano Ferracuti, Paolo Roma

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Abstract

Background: In the wake of the sudden spread of COVID-19, much of the Italian population practiced behaviors that were incongruous with the protective health measures promoted by the Italian government.

Objective: The present study aimed at examining psychological and psychosocial variables that could potentially predict behavioral compliance.

Methods: An online survey was administered from 18–22 March 2020. There were 2,766 participants (71.7% female, 28.3% male), with an average age of 32.94 years (SD = 13.2; range 18–90 years). Paired sample t-tests were run to compare efficacy perception with behavioral compliance. Mediation and moderated mediation models were constructed to explore the association between perceived efficacy and compliance, mediated by self-efficacy and moderated by risk perception and civic attitudes. Machine learning algorithms were trained on all of the collected psychosocial variables to predict which individuals would be more likely to comply with COVID-19 protective measures.

Results: The results indicated significantly lower scores in behavioral compliance (M = 41.7, SD = 6.20) relative to efficacy perception (M = 44.8, SD = 6.17). The introduction of risk perception and civic attitudes as moderators rendered the mediating effect of self-efficacy insignificant. The impact of perceived efficacy on the adoption of recommended behaviors varied in accordance with risk perception and civic engagement. The best pool of predictors (15 out of 199), identified using the correlation-based feature selector, produced a ROC area in the range of 0.83–0.93 for classifying individuals as high versus low compliance.

Conclusions: Government awareness communications and campaigns regarding COVID-19 and related protective measures should be tailored to specific segments of the population, as defined by age and level of education. Furthermore, they should emphasize the efficacy of the recommended measures in successfully preventing the virus spread. Finally, they should take into account risk perception and should highlight the importance of civic engagement. Clinical Trial: N/A

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HOW TO IMPROVE COMPLIANCE WITH PROTECTIVE HEALTH MEASURES DURING THE COVID-19 OUTBREAK:
TESTING A MODERATED MEDIATION MODEL AND MACHINE LEARNING ALGORITHMS

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Abstract

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Results: The results indicated significantly lower scores in behavioral compliance (M = 41.7, SD = 6.20) relative to efficacy perception (M = 44.8, SD = 6.17). The introduction of risk perception and civic attitudes as moderators rendered the mediating effect of self-efficacy insignificant. The impact of perceived efficacy on the adoption of recommended behaviors varied in accordance with risk perception and civic engagement. The 14 collected variables, which were entered as predictors in machine learning models, produced a ROC area in the range of 0.82–0.91 for classifying individuals as high versus low compliance.

Conclusions: Government awareness communications and campaigns regarding COVID-19 and related protective measures should be tailored to specific segments of the population, as defined by age and level of education. Furthermore, they should emphasize the efficacy of the recommended measures in successfully preventing the virus spread. Finally, they should take into account risk perception and should highlight the importance of civic engagement.

Keywords: COVID-19; compliance; efficacy, risk perception; civic engagement; personality

Introduction

Public willingness to comply with the protective health measures proposed by authorities is critical for controlling the outcomes of an infectious disease outbreak [1], given that "behavioral changes can significantly affect the epidemic spread both qualitatively […] and quantitatively" [2]. Coronavirus disease 2019 (COVID-19, also known as 2019-nCoV), an acute respiratory illness with an unknown cause, emerged in China in December 2019 and, since then, has spread rapidly throughout most of the world. In January 2020, the World Health Organization declared it an international public health emergency and, shortly thereafter, a global pandemic [3]. On 30 January 2020, the first two cases of COVID-19 in Italy were confirmed by the Italian government. In the following weeks and months, the health emergency generated devastating consequences for both local residents and national health workers. Due to the lack of supported treatments and vaccines, Italy (similar to other countries) implemented a policy of social and physical distancing, as well as a mandatory recommendation to "stay at home". However, the virus continued to escalate at an overwhelming rate, due in part to the failure of a large portion of Italian residents to observe the recommended health measures, despite the government's prevention information campaigns (issued from February onwards). To dissuade unsafe behaviors, the government was forced, on 19 March, to introduce penalties for those violating the guidance by leaving their domiciles for reasons other than stringent and absolute need. It is worth noting that, at this point in time, the contagion was already very advanced: on 18 March, the official cases reported by the government included 33,190 infected, 4,440 recovered, and 3,400 deceased [4,5].

The present research stemmed from the observation that, throughout this health crisis, Italian residents (similar to those in other affected countries) have engaged in incongruous behaviors, thereby severely limiting the effective management of COVID-19. To investigate this phenomenon more deeply, we selected and explored the effect of multiple psychological and psychosocial variables that were thought to relate to individual differences in compliance with the intervention measures and safety behaviors during the first phases of the COVID-19 outbreak in Italy.

Perceived Efficacy and Compliance

The belief that a recommended health behavior will have positive consequences and/or will reduce a public health threat (or its seriousness) is commonly defined as *perceived efficacy* or *perceived benefits*. In actuality, these terms indicate slightly different constructs, originating from different theoretical frameworks: the health belief model (HBM) [6] and protection motivation theory (PMT) [7,8], respectively. Although perceived benefits also include non–health-related positive outcomes (e.g., having more money after quitting smoking), the term is often used synonymously with perceived efficacy. In this study, we use the term *perceived efficacy* very specifically to describe people's perception of the efficacy of the recommended preventive measures in reducing the risk of contagion. Perceived efficacy has been studied in relation to a variety of general health measures, including engaging in physical activity, receiving vaccinations, and complying with medical treatment among psychiatric outpatients [9-11]; the literature suggests that it is a key determinant for compliance with preventive health behaviors and that "only when a person feels that the recommended behavior is likely to lead to the desired outcome will adoption of the recommendations occur" [12, p.193]. Perceived efficacy has also been studied in the context of past epidemics/pandemics (e.g., H1N1) and the current COVID-19 outbreak, demonstrating that it is one of the strongest predictors of compliance with preventive health behaviors [13-15].

The Mediating Role of Self-Efficacy

Self-efficacy is defined as "people's beliefs about their capabilities to produce designated levels of performance that exercise influence over events that affect their lives" [16, p.71]. Of note, the

concept also refers to an individual's belief about their ability to perform specific behaviors in particular situations [17]. A direct relationship between self-efficacy and behavioral change has been found in many health contexts (relating to, e.g., cigarette smoking, weight control, contraceptive behavior, alcohol abuse) [18,19] and during past pandemics [20], indicating a strong relationship between self-efficacy and health behavior change and maintenance. According to the health action process approach (HAPA) [21], three specific cognitions lead to an intention to act (i.e., motivation): (a) perceiving oneself as at risk (i.e., a risk perception), (b) believing that the recommended health behavior will reduce the threat (i.e., an efficacy perception), and (c) self-efficacy. Although efficacy perception has been found to be a stronger predictor than self-efficacy in developing the intention to act [22], "individuals need to know the contingencies between behaviors and outcomes […], but they also need to be confident that they can really perform the behavior in question" (p.493). Accordingly, the present study aimed at revealing whether self-efficacy plays a mediating role in this relationship. We posited that feeling able to perform the recommended health behaviors would mediate the relationship between the perceived efficacy of those measures and compliance.

Hypothesis 1: *Self-efficacy would mediate the relationship between the perceived efficacy of the government health measures and compliance (simple mediational model), even after controlling for age, education, and personality dysfunction. Higher levels of perceived efficacy would increase compliance through higher self-efficacy.*

The Moderating Role of Risk Perception

Risk perception, defined as an individual's belief about the risk of potential harm, is a key construct of many theoretical frameworks for health behaviors (e.g., HBM, PMT, HAPA). Risk perception is influenced by the perceived severity of the specific health threat and the perceived likelihood of harm. As noted by Brewer et al. [23], previous studies have often used the terms "likelihood" and "vulnerability"/"susceptibility" interchangeably, even though the first represents "one's probability of being harmed by a hazard under certain behavior conditions" (p.137), whereas the second can be defined as individual resistance or constitutional vulnerability.

Research on past epidemics/pandemics (e.g., H1N1) has not only shown risk perception to be a key driver of health behaviors, but it has also consistently found an association between risk perception and precautionary behaviors [24-26], even though a meta-analysis highlighted that this association involves only small effect sizes [23], especially with respect to perceived severity ($r = .16$).

Hypothesis 2: *Risk perception would moderate the relationship between the perceived efficacy of the government health measures and compliance (Hypothesis 2a), as well as the positive relationship between the perceived efficacy of the health measures and self-efficacy (Hypothesis 2b) and the positive relationship between self-efficacy and compliance (Hypothesis 2c) (moderated mediation models). Higher perceived efficacy of the health measures would be associated with increased compliance with protective health measures, especially alongside higher risk perception.*

The Moderating Role of Civic Engagement

Civic engagement can be defined as "the process of believing that one can and should make a difference in enhancing his or her community" [27]. It is typically thought to have two dimensions: attitudes and behaviors. However, since the present study was focused on cognitive variables, we primarily examined civic attitudes.

Due to the lack of a strong theoretical model for civic engagement in health contexts, no previous research has examined the link between civic engagement and health behaviors (or specifically, compliance with health measures). However, studies have focused on specific aspects of civic engagement, such as perceived moral responsibility. For example, a recent study [11] investigating the vaccination rate among nurses in Hong Kong considering HBM constructs and using perceived

moral responsibility as a moderator found an insignificant effect. Furthermore, previous studies have examined individuals' level of information regarding community health concerns during pandemics (including the current COVID-19 pandemic), demonstrating a positive association between knowledge about a specific threat and preventive behaviors [14,28,29]. These results suggest that promoting knowledge about COVID-19 might encourage the adoption of preventive behaviors. Therefore, we included this variable as a moderator because it could potentially provide insight into how to improve compliance to the recommended preventive behaviors.

Hypothesis 3: *Civic attitudes would moderate the relationship between the perceived efficacy of the government health measures and compliance (Hypothesis 3a), as well as the positive relationship between the perceived efficacy of the health measures and self-efficacy (Hypothesis 3b) and the positive relationship between self-efficacy and compliance (Hypothesis 3c) (moderated mediation models). Higher perceived efficacy of the health measures would be associated with increased compliance with the protective health measures, especially alongside higher levels of civic attitudes.*

The Role of Personality Dysfunction

We included level of personality dysfunction (as assessed by the DSM-5 approach [30]) as a control variable, as several studies have shown that people react differently to threats according to certain personality traits [31,32]. For instance, individuals with high levels of antagonism, which refers to aggressive tendencies accompanied by assertions of dominance and grandiosity, may argue with other people when their desires are not satisfied [33]. Moreover, high levels of disinhibition are commonly related to greater impulsivity and sensation seeking, which could lead to a tendency to ignore real dangers or threats. Despite the paucity of studies on personality variables and compliance with government recommendations during past pandemics, it is possible that higher levels of personality dysfunction could interfere with behavioral compliance.

Figure 1 shows the proposed moderated mediation model.

Fig. 1
Proposed moderated mediation model
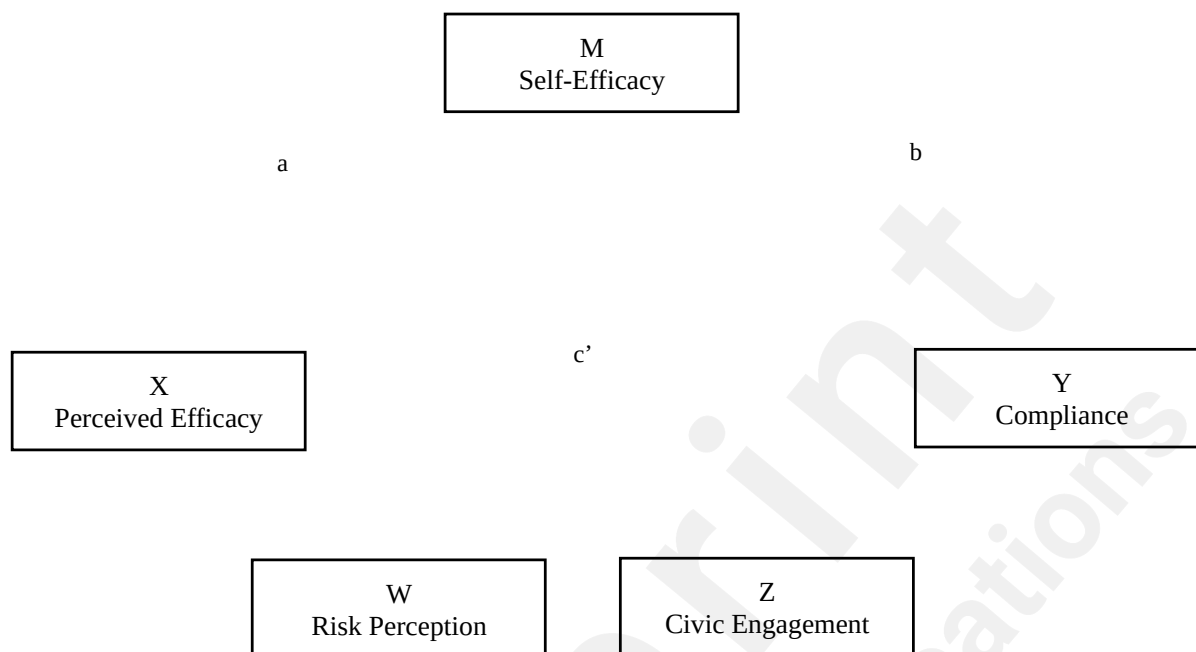
Predictive Models

Recently, researchers from a range of scientific fields (including the clinical and social sciences) have begun to emphasize the increased need to focus on prediction, rather than explanation, during data analysis [34]. Machine learning (ML) is a branch of artificial intelligence that focuses on data prediction. ML algorithms automatically learn information from a set of data and make predictions on unseen data without being explicitly programmed to do so. ML techniques have been shown to be particularly useful in predicting human behavior, including high-risk behavior [35]. Indeed, one of the main advantages of ML is that it enables inferences to be made at the individual level, whereas traditional statistical methods focus primarily on the group level [36]. Thus, ML predictive models support researchers in making predictions for individual subjects, which is particularly useful for the development of personalized and targeted prevention campaigns. In the present study, ML algorithms were applied to the 14 psychosocial variables to predict individuals' likelihood of complying with the COVID-19 protective measures.

We identified the predictive variables with maximal accuracy in classifying subjects as exhibiting high or low compliance with the protective health measures prescribed by the Italian government.

Materials and Methods
Procedures

The research team assembled an online survey inspired by the literature and collected data over five days (18–22 March 2020). The questionnaire was administered cross-sectionally on an online survey platform, which participants accessed via a designated link. The link was disseminated through the main means of communication and social networks, in order to reach a large number of subjects. The study was approved by the local ethics committee (Board of the Department of Human

Neuroscience, Faculty of Medicine and Dentistry, Sapienza University of Rome).

Measures

Behavioral compliance

Ten questions were designed to investigate compliance with the COVID-19 protective measures (e.g., "It is suggested that all persons avoid crowed places. Are you complying with this?"). These questions were assessed on a five-point Likert scale ranging from 1 (*slightly*) to 5 (*extremely*).

Perceived efficacy

When COVID-19 became pervasive, the Italian government announced guidelines for preventing infection, including "Disinfect hands often" and "Stay at home." Accordingly, 10 statements were provided to measure the perceived efficacy of 10 protective guidelines (e.g., "It is suggested that all persons avoid crowed places. Do you find this useful?") using a five-point Likert scale ranging from 1 (*hardly*) to 5 (*extremely*).

Self-efficacy

Participants' self-efficacy with respect to protecting themselves from COVID-19 was measured using three questions (e.g., "I am confident in my ability to protect myself from COVID-19") adapted from previously validated measures [20], which were assessed on a five-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Cronbach's alpha was an acceptable .62.

Risk perception

Risk perception was assessed through two variables, perceived severity and perceived likelihood, using items adapted from Cho and Lee [20] and Liao, Cowling, Lam, Ng, and Fielding [37]. Perceived severity was assessed using four items (e.g., "If I got COVID-19, it would be severe"), with a Cronbach's alpha of .70. Perceived likelihood was assessed using two items ("How likely is it that you will get COVID-19 in this period?"), with Cronbach's alpha of .80. Six questions were assessed on a five-point Likert scale ranging from 1 (*not likely at all*) to 5 (*certain*).

Civic engagement

The Civic Engagement Scale (CES) [27] was employed. The CES is a 14-item scale based on an understanding of civic engagement as "the process of believing that one can and should make a difference in enhancing his or her community." It measures two specific aspects of civic engagement: attitudes and behaviors. The first subscale (Attitudes), composed of eight items, assesses civic attitudes in terms of "the personal beliefs and feelings that individuals have about their own involvement in their community and their perceived ability to make a difference in that community". The second subscale (Behaviors), composed of six items, assesses civic behaviors in terms of "the actions that people take to actively attempt to engage and make a difference in their community". Both the Attitudes and the Behaviors subscale obtained high reliability in the validation study, with Cronbach's alphas of .91 and .85, respectively. In the present sample, Cronbach's alpha was .87 for both scales, and each item was assessed on a five-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).

Personality dysfunction

Personality dysfunction was investigated using the Personality Inventory for DSM-5—Brief Form—Adult (PID-5-BF) [38]. The PID-5-BF is a 25-item self-rated personality traits assessment. It measures five personality trait domains: negative affect, detachment, antagonism, disinhibition, and psychoticism. Each domain is measured through five items, which are rated on a four-point Likert scale ranging from *0* (*very false or often false*) to 3 (*very true or often true*). The overall measure generates scores in the range 0–75, with higher scores indicating greater overall personality dysfunction. Each trait domain receives a score in the range 0–5, with higher scores indicating greater dysfunction in that specific personality trait domain.

Participants

A total of 2,812 respondents participated in the survey. All participants were aged 18 years or older and were living in Italy. The online survey was closed on the sixth day following dissemination of

the link. All participants voluntarily responded to the anonymous survey and indicated their informed consent within the survey. The procedures were clearly explained, and participants could interrupt or quit the survey at any point without explaining their reasons for doing so. Two respondents were excluded from the sample because they were younger than 18 years, and 44 participants were excluded because they lived outside of Italy during the outbreak.

The final sample consisted of 2,766 participants: 1,982 (71.7%) females and 784 (28.3%) males. The mean age of the sample was 32.94 (13.2; range 18–90 years) and the majority were Italian citizens (N = 2,739, 99%). Most of the sample (N = 1,194, 43.2%) held a high school degree and were unmarried (N = 1,866, 67.5%), unemployed (N = 1,165, 42.1%), and childless (N = 2,130, 77%). Furthermore, most participants reported to stay at home (N = 2,368, 85.6%) and going out up to one time per day (N = 2,559, 92.5%).

Statistical Analysis

A paired sample t-test was used to compare efficacy perception with behavioral compliance. Cohen's *d* [39] effect size was inspected for each significant effect.

The mediation and moderated mediation models were run using PROCESS version 3.5 [40], as developed by Preacher and Hayes [41] for SPSS, version 25 (IBM, Armonk, NY). Moderated mediation tests simple mediation models (i.e., determining whether a given variable or mediator accounts for some or all of the relationship between two other variables) that may differ according to a further variable (e.g., if the mediation pathway is only present for individuals with higher or lower levels of certain variables). PROCESS estimates indirect effects (i.e., mediation) and conditional indirect effects (i.e., moderated mediation) using bootstrap confidence intervals. In the present study, the bias-corrected 95% confidence interval (CI) was calculated using 5,000 bootstrapping resamples. Effects were considered significant if the resulting CI did not contain 0. All measures, including compliance with protective health measures, were treated as continuous variables except for the ordinal covariate "education". Considering PROCESS model templates [42], we first tested a simple mediation model (Model 4) to explore if the association between perceived efficacy of the recommended health measures and compliance was mediated by self-efficacy. Next, we tested Model 76 to verify the moderated effect of risk perception and civic attitudes on the direct and indirect effects of the perceived efficacy of the health measures on compliance. "High" and "low" levels of both moderators were determined at one standard deviation above and below the mean of each scale. Both models controlled for age, education, and level of personality dysfunction. Finally, ML models were trained and tested in WEKA 3.9 [43]. The procedure used to build the models is reported in the "Results" section.

Results

Descriptive statistics and scale correlations are reported in Table 1.

Tab. 1. Descriptive statistics and intercorrelations

Dimensions	*M*	*SD*	1	2	3	4
1. Compliance	41.66	6.20	-			
2. Perceived efficacy	44.82	6.17	.742**	-		
3. Self-efficacy	12.55	1.71	.332**	.198**	-	
4. Perceived risk	18.56	3.18	.129**	.218**	−.077**	-
5. Civic attitudes	42.33	8.52	.191**	.176**	.243**	.118**

Note: p <.01**.

Paired sample t-test

A paired sample t-test was conducted to investigate differences between the perceived efficacy of the recommended safety behaviors and compliance. The result was statistically significant, $t(2,765) = 37.384$, $p < .001$, with an effect size (= .711) approaching Cohen's [39] standard for a large effect (= .80). The results further indicated a statistically significant reduction in scores for behavioral compliance ($M = 41.7$, $SD = 6.20$) relative to perceived efficacy ($M = 44.8$, $SD = 6.17$). Subsequent paired sample t-tests were run for each safety measure prescribed by the Italian government (e.g., "Avoid hugs," "Avoid handshakes," etc.). T-test results were significant for all protective measures except for "Avoid handshakes": $t(2,765) = 1.253$, $p < .210$, $d = .024$ (see Multimedia Appendix A1 for more information).

Mediation Model

Hypothesis 1 postulated that self-efficacy would mediate the relationship between the perceived efficacy of the recommended health measures and compliance. As shown in Table 2, the total effect of perceived efficacy on compliance was significant ($B = .750$ [$SE = .01$] $p < .001$ [$CI = .725, .775$]). The mediation analyses showed that the indirect effect of perceived efficacy on compliance via self-efficacy was positive (.034) and the bootstrapped 95% CI did not include 0 [.026, .044]. Furthermore, the covariates age, education, and personality dysfunction were significant: the first showed a positive association with behavioral compliance, whereas the others showed a negative association with the outcome variable. The final mediation model explained 60% of the total variance in compliance with the health measures: 97% of the total effect on compliance was explained by the direct effect of perceived efficacy, whereas 3% was explained by the indirect effect of the mediator.

Tab. 2. Mediation results ($N = 2,766$)

Predictors	β	t	p	95% CI LL	95% CI UL
Model 1 (DV: Self-efficacy)					
Covariates					
Age	−.00	−.25	.800	−.005	.004
Education	**−.12**	**−2.88**	**.004**	**−.205**	**−.039**
Personality dysfunction	**−.03**	**−8.25**	**<.001**	**−.031**	**−.019**
Independent variable					
PE	**.05**	**10.23**	**<.001**	**.043**	**.063**
			$R^2 = .06$		
			$F(4, 2761) = \mathbf{46.69^{***}}$		
Model 2 (DV: Compliance)					
Covariates					
Age	**.04**	**6.49**	**<.001**	**.026**	**.049**
Education	**−.27**	**−2.68**	**.008**	**−.467**	**−.072**
Personality dysfunction	**−.04**	**−5.75**	**<.001**	**−.057**	**−.028**
Independent variables					
SE	**.65**	**14.38**	**<.001**	**.561**	**.738**
PE	**.72**	**57.44**	**<.001**	**.691**	**.740**
			$R^2 = .60$		
			$F(5, 2760) = \mathbf{826.83^{***}}$		

Notes. PE = perceived efficacy of the recommended health measures; SE = self-efficacy. Bootstrap sample size = 5,000 (two-tailed); significant values outlined in bold. $p < .001^{***}$.

Moderated Mediation Model

The results of the moderated mediation model related to conditional indirect effects, as presented in Table 3. Hypothesis 2 was partially confirmed: risk perception emerged as a significant moderator in the relationship between the perceived efficacy of the recommended health measures and compliance (Hypothesis 2a), whereas no moderation effects of this variable emerged in either the relationship between perceived efficacy and self-efficacy or the relationship between self-efficacy and compliance (Hypotheses 2b and 2c).

Similar results were found for the moderating role of civic attitudes. As shown in Table 3, this variable moderated the direct effect of perceived efficacy on compliance (Hypothesis 3a). However, no significant effects were found in the relationship between perceived efficacy and self-efficacy or the relationship between self-efficacy and compliance (Hypotheses 3b and 3c).

Further, older age, higher educational levels, and lower personality dysfunction emerged as significant covariates that were positively associated with higher behavioral compliance.

As shown in Figure 2, the simple slope analysis found that the positive relationship between perceived efficacy and behavioral compliance was significant (B = .78, p < .001) under both high (+1 SD) and low levels of perceived risk (-1 SD) (B = .70, p < .001). Similarly, the positive relationship between perceived efficacy and behavioral compliance was significant (B = .78, p < .001) under both high and low levels of civic attitudes (B = .70, p < .001).

Tab. 3. Moderated mediation results (N = 2,766)

Predictors	β	t	p	95% CI	
				LL	UL
Model 1 (DV: Self-efficacy)					
Covariates					
Age	−.00	−1.29	.198	−.008	.002
Education	**−.12**	**−2.89**	**.004**	**−.201**	**−.038**
Personality dysfunction	**−.02**	**−7.45**	**<.001**	**−.028**	**−.016**
Independent variables					
PE	**.07**	**2.50**	**.013**	**.015**	**.126**
Risk perception	−.08	−1.34	.179	−.206	−.038
PE x Risk perception	.00	.001	.846	−.002	.003
CE attitudes	**.07**	**3.15**	**.002**	**.027**	**.117**
PE x CE attitudes	−.00	−1.23	.217	−.002	.000
			R^2 = .12		
			F(8, 2757) = **48.08*****		
Model 2 (DV: Compliance)					
Covariates					
Age	**.04**	**6.53**	**<.001**	**.027**	**.050**
Education	**−.25**	**−2.51**	**.012**	**−.453**	**−.056**
Personality dysfunction	**−.04**	**−5.44**	**<.001**	**−.056**	**−.025**
Independent variables					
SE	.52	1.69	.092	−.085	1.132
PE	**.34**	**4.74**	**<.001**	**.196**	**.473**
SE x Risk perception	−.00	−0.14	.885	−.029	.025
SE x CE attitudes	.01	0.80	.422	−.005	.013
Risk perception	**−.53**	**−2.52**	**.012**	**−.952**	**−.119**
PE x Risk perception	**.01**	**3.56**	**<.001**	**.005**	**.019**

CE attitudes	−.23	−3.09	.002	−.370	−.083
PE x CE attitudes	.01	3.34	.001	.002	.007

$$R^2 = .61$$
$$F(11, 2754) = \mathbf{382.97^{***}}$$

Notes. PE = perceived efficacy of the recommended health measures; CE = civic engagement; SE = self-efficacy. Bootstrap sample size = 5,000 (two-tailed); significant values outlined in bold. $p < .001^{***}$.

Fig. 2
Simple slope analysis of the effect of perceived risk and civic attitudes on the relationship between perceived efficacy and compliance
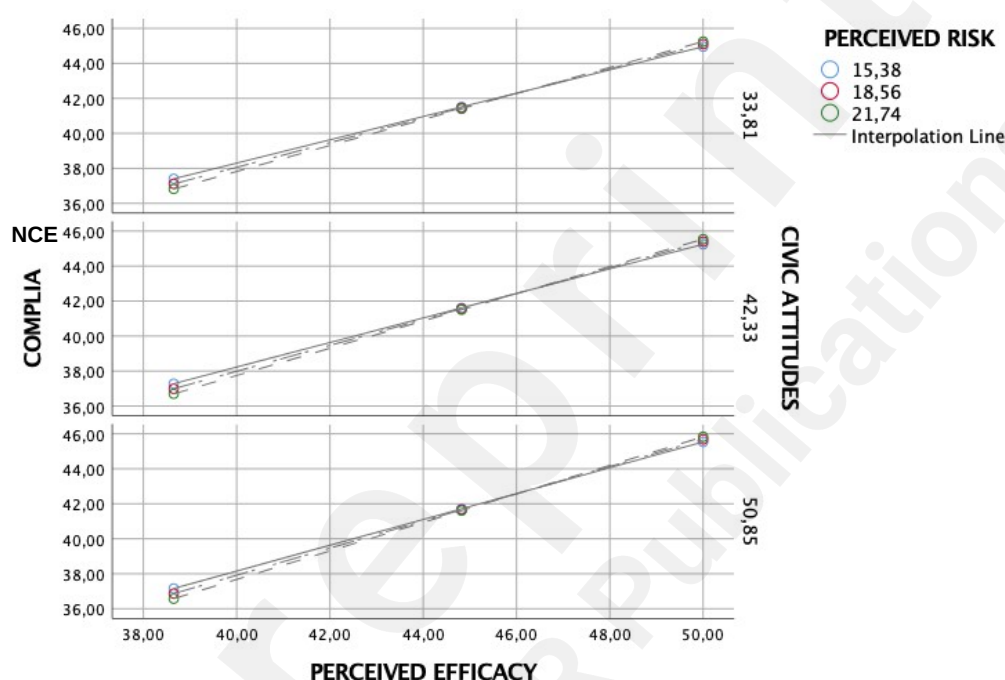
Machine Learning
To predict individuals' compliance with the COVID-19 protective measures based on the collected psychosocial variables, participants were split into two classes: *high compliance* and *low compliance*. The low compliance class included participants with a total compliance score (i.e., sum of the scores of items concerning application of the safety measures) ≤ 30 ($N = 171$); the high compliance class included participants with a total compliance score > 30 ($N = 2,595$).
We followed the recommended procedure to ensure model generalization and to increase the replicability of the results, by splitting the data into two sets: a training set (used to train and validate the model) and a test set (used to test model accuracy on examples that had never been seen by the ML classifier) [36,44]. In the present study, a percentage split of 80:20 training to test data was applied, with participants randomly assigned to one or the other set while maintaining the proportion between classes. Therefore, the training set consisted of 2,213 participants (2,076 high compliance and 137 low compliance) and the test set consisted of 553 participants (519 high compliance and 34 low compliance).
All the 14 collected variables were entered in the ML models as predictors: gender, age, education, work position, marital status, citizenship, child(ren), home/work, going out per day, self-efficacy, risk perception, civic attitudes, perceived efficacy, personality disfunction. Using these 14 predictors, ML algorithms were run and validated on the training sample ($N = 2,213$) using a 10-fold cross-

validation procedure. Specifically, k-fold cross-validation was used; this resampling procedure seeks to reduce variance in the model performance estimation by using a single training set and a single test set. It portions the sample into k = 10 subsets (folds), using 9 of them to train the model and the remaining subset to validate its accuracy. This procedure is repeated k = 10 times, with 1 fold left out each time as a validation set [45]. The final model metrics are obtained by averaging the metrics of the k = 10 validation subsets. Finally, the models developed through the 10-fold cross-validation were tested on the test sample (N = 553). Specific ML algorithms were selected to represent different classification strategies: logistic regression [46], support vector machine [47], naïve Bayes [48], and random forest [49]. This ensured that the results were stable across classifiers and did not depend on specific model assumptions.

In running the classification algorithms, the class imbalance problem was addressed. ML methods work best with balanced datasets—a condition that is rarely met within scientific research with human subjects [50]. A different number of instances across classes may lead to an overall correct classification into the majority class and a complete misclassification of instances into the minority class. In the present research, the two classes were extremely unbalanced, with a ratio of 1:15 between the high compliance and low compliance groups. One strategy to overcome class imbalance consists of altering the relative costs associated with misclassifying the minority and majority classes, in order to compensate for the imbalance [51]. Following this methodology, in the present study, the ML algorithms were designed in such a way that an error in classifying the minority class (low compliance) was weighted 15 times more than an error in classifying the majority class (high compliance). This cost-modifying strategy has been shown to provide better results in addressing class imbalance than other methods, such as random oversampling of the minority class or random undersampling of the majority class [51]. Moreover, it should be noted that, for the goal of this task, it was more beneficial to obtain a lower number of false negatives than false positives; likewise, it was more beneficial to have a model with high sensitivity rather than high specificity. In other words, it was more important to not miss people with low compliance than to misclassify people as high compliance.

The final classification results of the 10-fold cross-validation and test set are reported in Tables 4 and 5, respectively. The models' predictive performance was quantified using the following metrics: ROC area, accuracy, precision, recall (or sensitivity), and F-measure (F1 score). Of note, the classifiers showed a ROC area in the range of 0.82–0.91 in the test set. However, random forest and naïve Bayes classifiers highlighted a lower recall for *low compliance* compared to other classifiers, making them weaker models for the purposes of prediction.

Finally, to investigate the weight of the 14 predictors in the models, here we report the point-biserial correlation (r_{pb}) between the outcome and each predictor: perceived efficacy=.547, self-efficacy=.173, age=.104, going out per day=.101, perceived risk= .100, civic attitudes=.095, work/home= .080, child(ren)=.079, education=.077, marital status=.076, personality dysfunction =.072, gender=.060, work position =.057, citizenship=.029.

Tab. 4. Metrics of the ML models trained and validated using 10-fold cross-validation

Algorithm	Accuracy	ROC area	Class	Precision	Recall	*F*-measure
Logistic	88.07%	0.941	*High compliance*	0.990	0.882	0.933
			Low compliance	0.325	0.861	0.904
SVM	88.89%	0.871	*High compliance*	0.990	0.880	0.932
			Low compliance	0.322	0.861	0.468

	Accuracy	ROC area	Class	Precision	Recall	F-measure
Random forest	95.71%	0.938	High compliance	0.976	0.979	0.977
			Low compliance	0.662	0.628	0.644
Naive Bayes	94.35%	0.929	High compliance	0.978	0.916	0.970
			Low compliance	0.534	0.679	0.598

Tab. 5. Metrics of the ML models tested on 553 new participants (test set)

Algorithm	Accuracy	ROC area	Class	Precision	Recall	*F*-measure
Logistic	86.62%	0.918	High compliance	0.983	0.873	0.942
			Low compliance	0.283	0.765	0.413
SVM	87.34%	0.823	High compliance	0.983	0.881	0.929
			Low compliance	0.295	0.765	0.426
Random forest	94.39%	0.901	High compliance	0.964	0.977	0.970
			Low compliance	0.556	0.441	0.492
Naive Bayes	94.03%	0.875	High compliance	0.969	0.967	0.968
			Low compliance	0.514	0.529	0.522

Discussion

Public willingness to comply with the protective health measures proposed by authorities is critical for controlling the outcomes of an infectious disease outbreak. The situation in many countries during the current COVID-19 pandemic indicates that, despite legal penalties and mass information campaigns, not all citizens have adopted the recommended behaviors to prevent the spread of the virus. Thus, the present study sought to identify which psychological and psychosocial factors might improve compliance.

The results confirmed our first hypothesis, showing that self-efficacy significantly mediated the relationship between perceived efficacy and compliance. Stated differently, our findings suggest that individuals who perceive themselves as able to carry out (i.e., those with self-efficacy) those behaviors judged as effective in reducing the threat (i.e., behaviors with perceived efficacy) are more likely to comply with the government measures. This finding highlights the key role of self-efficacy in the adoption and maintenance of recommended health actions [19] and suggests a relationship between self-efficacy and compliance with the preventive measures during the COVID-19 pandemic, as previously reported for different populations (e.g., healthcare workers) [52,53]. Furthermore, some covariates were also significant: older age, lower education levels, and lower levels of personality dysfunction were all associated with increased compliance. These results parallel preliminary findings on the COVID-19 outbreak, indicating that younger persons and those with higher education levels are less likely to comply with the recommended measures, especially those related to hygiene [54]. To the best of our knowledge, this study represents the first attempt to provide data on the association between personality functioning and compliance with health measures. The findings suggest that overall personality functioning may be significant in influencing individuals to adopt the protective measures recommended by authorities. For this reason, personality functioning should be assessed more frequently, and those already known to have a

personality impairment (e.g., clinical patients) should be supported and controlled more promptly than others.

Our second and third hypotheses were only partially confirmed: on the one hand, risk perception and civic attitudes as moderators made the mediation of self-efficacy insignificant, thereby invalidating Hypotheses 2b, 2c, 3b, 3c. With respect to this unexpected result, we propose that the two relevant moderators made self-efficacy less important in influencing compliance with the health measures; however, further research investigating the associations between these variables is recommended. On the other hand, both risk perception and civic attitudes were found to significantly moderate the relationship between perceived efficacy and compliance. Thus, the impact of perceived efficacy on compliance varied in accordance with risk perception and civic attitudes, thereby confirming Hypotheses 2a and 3a. As the moderation coefficient for both constructs was positive, higher risk perception and civic attitudes were associated with a stronger effect of perceived efficacy on compliance. Regarding risk perception, this result is in line with previous studies reporting a strong association between risk perception and changes in (or maintenance of) health behaviors in a variety of contexts, including epidemic/pandemics [24-26,55]. With respect to civic attitudes, this is a novel finding of our study, as such attitudes have not previously been studied in the context of pandemic behavioral responses. The current finding of a link between civic attitudes and preventive health actions suggests the importance, for instance, of teaching civic education in the early school grades.

Finally, as regards the ML classification models outcome, it has been shown that the above-mentioned psychological and psychosocial variables are able to predict which individuals have high versus low compliance, with a ROC area in the range of 0.82–0.91 and high sensitivity for the target class (low compliance). Taken together, the results of the moderated mediation and ML models underline that the most important variable for compliance with the recommended health behaviors is perceived efficacy, as has been consistently indicated by previous studies on behavioral responses to epidemics [13-15,26]. This result suggests that, to foster compliance, communications regarding COVID-19 containment measures should focus on perceived efficacy by highlighting the utility of the recommended behaviors.

The present results should be interpreted with caution, due to some limitations. First, the cross-sectional study design, implemented during the first phases of the COVID-19 outbreak in Italy, prevented us from drawing causal inferences. We were unable to assess individuals' psychological functioning before the virus spread, and we were similarly unable to report behavioral compliance with the recommended health measures in more advanced phases of the outbreak. Further, the data collection via a web-based survey relied on voluntary sampling and self-reported data; thus, the data may be distorted by selection or social desirability biases.

Despite these limitations, our findings have several significant implications due to the lack of relevant research on targeted interventions to enhance public compliance with government health recommendations during the COVID-19 outbreak. Countries affected by COVID-19 should consider relevant psychological dimensions alongside their lockdown protocols. In particular, government strategists may use the findings of the present study on the psychological characteristics of people who do and do not comply with the containment measures (i.e., perceived efficacy, risk perception, civic attitudes) to target their COVID-19 communications more effectively. Overall, we believe that our findings will be helpful in guiding age-tailored information/advertising campaigns in countries affected by COVID-19 and directing further research on behavioral compliance.

Conflicts of Interest
None declared.

Multimedia Appendix
Table A1.

References

1. van der Weerd W, Timmermans DR, Beaujean DJ, Oudhoff J, van Steenbergen JE. Monitoring the level of government trust, risk perception and intention of the general public to adopt protective measures during the influenza A (H1N1) pandemic in the Netherlands. *BMC Public Health* 2011 Jul;11(1):575. doi:10.1186/1471-2458-11-575. PMID:21771296

2. Poletti P, Ajelli M, Merler S. The effect of risk perception on the 2009 H1N1 pandemic influenza dynamics. *PLOS One*. 2011 Feb;6(2):e16460. doi:10.1371/journal.pone.0016460. PMID:21326878

3. World Health Organization. Statement on the second meeting of the International Health Regulations (2005) Emergency Committee regarding the outbreak of novel coronavirus (2019-nCoV), 2020. Retrieved from https://www.who.int/news-room/detail/30-01-2020-statement-on-thesecond-meeting-of-the-international-health-regulations-(2005)-emergency-committee-regarding-the-outbreak-of-novel-coronavirus-(2019-ncov)

4. Mazza C, Ricci E, Biondi S, Colasanti M, Ferracuti S, Napoli C, Roma P. A nationwide survey of psychological distress among Italian People during the COVID-19 pandemic: Immediate psychological responses and associated factors. *International Journal of Environmental Research and Public Health* 2020;17(9):3165. https://doi.org/10.3390/ijerph17093165

5. Fontanesi L, Marchetti D, Mazza C, Di Giandomenico S, Roma P, Verrocchio MC. The effect of the COVID-19 lockdown on parents: a call to adopt urgent measures. *Psychological Trauma: Theory, Research, Practice and Policy* (in press). https://dx.doi.org/10.1037/tra0000672

6. Becker MH. The health belief model and sick role behavior. *Health Education Monographs* 1974 Dec;*2*(4):409-419. doi:10.1177%2F109019817400200407.

7. Rogers RW. A protection motivation theory of fear appeals and attitude change. *Journal of Psychology* 1975;91(1):93-114. doi:10.1080/00223980.1975.9915803. PMID:28136248

8. Rogers RW. Cognitive and psychological processes in fear appeals and attitude change: A revised theory of protection motivation. In: Cacioppo JT, Petty RE, editors. *Social psychophysiology: A sourcebook.* New York: Guilford Press; 1983. p. 153-76. ISBN: 0898626269

9. Kelly GR, Mamon JA, Scott JE. Utility of the health belief model in examining medication

compliance among psychiatric outpatients. *Social Science & Medicine* 1987;25(11):1205-1211. doi:10.1016/0277-9536(87)90367-4. PMID:2893455

10. Brown SA. Measuring perceived benefits and perceived barriers for physical activity. *American Journal of Health Behavior* 2005 Mar;29(2):107-116. doi:10.5993/AJHB.29.2.2. PMID:15698978

11. Mo PK, Wong CH, Lam EH. Can the health belief model and moral responsibility explain influenza vaccination uptake among nurses? *Journal of Advanced Nursing* 2018 Oct;75(6):1188-1206. doi:10.1111/jan.13894. PMID:30375040

12. Block LG, Keller PA. When to accentuate the negative: The effects of perceived efficacy and message framing on intentions to perform a health-related behavior. *Journal of Marketing Research* 1995 May;32(2):192-203. doi:10.1177%2F002224379503200206.

13. Rubin GJ, Amlôt R, Page L, et al. Public perceptions, anxiety and behaviour change in relation to the swine flu outbreak: A cross sectional telephone survey. *Br Medical J* 2009 Jul; 339: b2651. doi:10.1136/bmj.b2651. PMID: 19574308

14. Rezaeipandari H, Mirkhalili SM, Sharifabad MAM, Ayatollahi J, Fallahzadeh H. Study of H1N1 influenza preventive behaviors predictors based on health belief model in Jiroft people. *Qom Univ Med Sci J* 2018 May;12(3):76-86. doi:10.29252/qums.12.3.76.

15. Pollak Y, Dayan H, Shoham R, Berger I. Predictors of adherence to public health instructions during the COVID-19 pandemic. *medRxiv* 2020 May. doi:10.1101/2020.04.24.20076620.

16. Bandura A. Self-efficacy. In: Ramachaudran VS, editor. *Encyclopedia of Human Behavior.* Vol. 4. New York: Academic Press; 1994. p. 71-81. ISBN: 0122269209

17. Schunk DH, Carbonari JP. Self-efficacy models. In: Matarazzo JD, Miller JH, Weiss S, editors. *Behavioral health: A handbook of health enhancement and disease prevention*. New York: Wiley; 1984. p. 230-47. ISBN: 0471869759

18. Stretcher V, DeVellis M, Becker M, Rosenstock I. Self-efficacy and the health belief model. *Health Education Quarterly* 1986;13:73-92.

19. Siela D, Wieseke AW. Stress, Self-Efficacy, and Health. In: Rice VH, editor. *Handbook of stress, coping, and health: Implications for nursing research, theory, and practice*. Los Angeles, CA: SAGE; 2011. ISBN: 1483306224

20. Cho H, Lee JS. The influence of self-efficacy, subjective norms, and risk perception on behavioral intentions related to the H1N1 flu pandemic: A comparison between Korea and the US. *Asian J Soc Psychol* 2015 Jun;18(4):311-324. doi:10.1111/ajsp.12104.

21. Schwarzer R. Self-efficacy in the adoption and maintenance of health behaviors: Theoretical

approaches and a new model. In: Schwarzer R, editor. *Self-efficacy: Thought control of action*. Washington, DC: Hemisphere; 1992. p. 217-42. ISBN: 131776370X

22. Schwarzer R, Renner B. Social-cognitive predictors of health behavior: Action self-efficacy and coping self-efficacy. *Health Psychology* 2000;19(5):487. doi:10.1037/0278-6133.19.5.487. PMID:11007157

23. Brewer NT, Chapman GB, Gibbons FX, Gerrard M, McCaul KD, Weinstein ND. Meta-analysis of the relationship between risk perception and health behavior: The example of vaccination. *Health Psychol* 2007;26(2):136. doi:10.1037/0278-6133.26.2.136. PMID:17385964

24. Bults M, Beaujean DJ, de Zwart O, et al. Perceived risk, anxiety, and behavioural responses of the general public during the early phase of the Influenza A (H1N1) pandemic in the Netherlands: Results of three consecutive online surveys. *BMC Public Health* 2011 Jan;11(1):2. doi:10.1186/1471-2458-11-2. PMID: 21199571

25. Katz R, May L, Sanza M, Johnston L, Petinaux B. H1N1 preventive health behaviors in a university setting. *J Am Coll Health* 2012 Dec;60(1):46-56. doi:10.1080/07448481.2011.570398. PMID: 22171729

26. Lau JT, Griffiths S, Choi KC, Lin C. Prevalence of preventive behaviors and associated factors during early phase of the H1N1 influenza epidemic. *Am J Infect Control* 2010 Jun;38(5):374-380. doi:10.1016/j.ajic.2010.03.002. PMID: 20569849

27. Doolittle A, Faul, AC. Civic engagement scale: A validation study. *SAGE Open* 2013 Jul;3(3):1-7. doi:10.1177%2F2158244013495542

28. Kwok KO, Li KK, Chan HH, Yi YY, Tang A, Wei WI, Wong YS. Community responses during the early phase of the COVID-19 epidemic in Hong Kong: Risk perception, information exposure and preventive measures. *Emerg Infect Dis* 2020 Jul;7(26). doi:10.3201/eid2607.200500

29. Li JB, Yang A, Dou K, Wang LX, Zhang MC, Lin X. Chinese public's knowledge, perceived severity, and perceived controllability of the COVID-19 and their associations with emotional and behavioural reactions, social participation, and precautionary behaviour: A national survey. *PsyArXiv* 2020 Feb. doi:10.31234/osf.io/5tmsh.

30. American Psychiatric Association. *Diagnostic and Statistical Manual of Mental Disorders.* 5th edition (DSM-5). Washington, DC: American Psychiatric Association; 2013. ISBN: 978-0-89042-554-1

31. Ioannou MC, Mogg K, Bradley BP. Vigilance for threat: Effect of anxiety and defensiveness.

Personal Individ Differ. 2004 Jun;36:1879-1891. doi:10.1016/j.paid.2003.08.018

32. Oathes DJ, Squillante CM, Ray WJ, Nitschke JB. The impact of worry on attention to threat. *PLoS ONE*. 2010 Oct;5(10):e13411. doi:10.1371/journal.pone.0013411. PMID: 20976238

33. Harkness AR, Reynolds SM, Lilienfeld SO. A review of systems for psychology and psychiatry: Adaptive systems, personality psychopathology five (PSY-5), and the DSM-5. *J Pers Assess* 2014 Aug;96(2):121-139. doi:10.1080/00223891.2013.823438. PMID: 23941204

34. Yarkoni T, Westfall J. Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspect Psychol Sci* 2017 Nov;12(6):1100-1122. doi:10.1177/1745691617693393. PMID: 28841086

35. Dwyer DB, Falkai P, Koutsouleris N. Machine learning approaches for clinical psychology and psychiatry. *Annu Rev Clin Psychol* 2018 May;14(1):91-118. doi:10.1146/annurev-clinpsy-032816-045037. PMID: 29401044

36. Orrù G, Monaro M, Conversano C, Gemignani A, G. Sartori G. Machine learning in psychometrics and psychological research. *Front Psychol* 2020 Jan;10:2970. doi:10.3389/fpsyg.2019.02970 PMID: 31998200

37. Liao Q, Cowling BJ, Lam WW, Ng DM, Fielding R. Anxiety worry and cognitive risk estimate in relation to protective behaviors during the 2009 influenza A/H1N1 pandemic in Hong Kong: Ten cross-sectional surveys. *BMC Infectious Diseases* 2014 Mar;14(1):169. doi:10.1186/1471-2334-14-169. PMID: 24674239

38. Krueger RF, Derringer J, Markon KE, Watson D, Skodol AE. *The Personality Inventory for DSM-5—Brief Form (PID-5-BF)—Adult*. Washington, DC: American Psychiatric Association, 2013.

39. Cohen J. *Statistical Power Analysis for the Behavioral Sciences*. 2nd edition. Hillsdale, NJ: Erlbaum; 1988.

40. Hayes AF. Partial, conditional, and moderated moderated mediation: Quantification, inference, and interpretation. *Communication Monographs* 2018;85(1):4-40. doi:10.1080/03637751.2017.1352100

41. Preacher KJ, Hayes AF. SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, & Computers* 2004 Nov;36(4):717-731. doi:10.3758/BF03206553. PMID: 15641418

42. Hayes AF. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A RegressionBased Approach*. New York, NY: Guilford Press, 2013. ISBN: 146253466X

43. Hall M, Holmes FE, Pfahringer G, Reutemann BP, Witten IH. The WEKA data mining

software: An update. *ACM SIGKDD Explor. Newsl* 2009 Nov;11(1):10-18. doi:10.1145/1656274.1656278

44. Dwork C, Feldman V, Hardt M, Pitassi T, Reingold O, Roth A. The reusable holdout: Preserving validity in adaptive data analysis. *Science* 2015 Aug;349(6248):636-638. doi:10.1126/science.aaa9375. PMID: 26250683

45. Kohavi R, editor. A study of cross-validation and bootstrap for accuracy estimation and model selection. *Proceedings of the 14th International Joint Conference on Artificial Intelligence* 1995 Aug;2(12):1137-43.

46. le Cessie S, van Houwelingen JC. Ridge estimators in logistic regression. *Appl Stat* 1992;41(1):191-201. doi:10.2307/2347628

47. Keerthi SS, Shevade SK, Bhattacharyya C, Murthy KRK. Improvements to Platt's SMO algorithm for SVM classifier design. *Neural Comput* 2001 Mar;13(3):637-649. doi:10.1162/089976601300014493

48. John GH, Langley P, editors. Estimating continuous distributions in Bayesian classifiers. *Proceeding of the 11th Conference on Uncertainty in Artificial Intelligence* 1995: 338-45.

49. Breiman L. Random forest. *Mach. Learn* 2001;45(1):5-32.

50. Japkowicz N, editor. The class imbalance problem: Significance and strategies. *Proceedings of the 2000 International Conference on Artificial Intelligence (ICAI)* 2000 Jun;111-17.

51. Japkowicz N, Stephen S. The class imbalance problem: A systematic study. *Intell Data Anal* 2002 Nov;6(5):429-49. doi:10.3233/IDA-2002-6504

52. Barati M, Bashirian S, Jenabi E, et al. Factors associated with preventive behaviours of COVID-19 among hospital staff in Iran in 2020: An application of the protection motivation theory [published online ahead of print, 2020 Apr 28]. *J Hosp Infect*. 2020;S0195-6701(20)30210-3. doi:10.1016/j.jhin.2020.04.035. PMID:32360337

53. Kebede Y, Yitayih Y, Birhanu Z, Mekonen S, Ambelu A. Knowledge, perceptions and preventive practices towards COVID-19 early in the outbreak among Jimma University Medical Center visitors, Southwest Ethiopia. *PLOS One* 2020 May;15(5):e0233744. doi:10.1371/journal.pone.0233744. PMID: 32437432

54. Nivette A, Ribeaud D, Murray AL, Steinhoff A, Bechtiger L, Hepp U, Shanahan L, Eisner M. Non-compliance with COVID-19-related public health measures among young adults: Insights from a longitudinal cohort study. 2020 May. doi:10.31235/osf.io/8edbj

55. Ibuka Y, Chapman GB, Meyers LA, Li M, Galvani AP. The dynamics of risk perceptions and precautionary behavior in response to 2009 (H1N1) pandemic influenza. *BMC Infectious*

Diseases 2010 Oct;10(1):296. doi:10.1186/1471-2334-10-296. PMID:20946662.

Abbreviations
CFS: correlation-based feature selector;
HBM: health belief model;
PMT: protection motivation theory;
HAPA: health action process approach;
ML: machine learning;
CES: civic engagement scale;
PID-5-BF: Personality Inventory for DSM-5 – Brief Form – Adult.

Supplementary Files

Multimedia Appendixes