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Exploring the predictors of health-protective behavior during the COVID-19 pandemic: A multi-country comparison

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ABSTRACT

In recent years, examining the determinants of health behaviors on a multi-country level remains limited. Therefore, the purpose of this study is to explore the key factors that may enhance the adoption of health-protective behaviors during the COVID-19 pandemic in Morocco and India. A theoretical framework derived from the health belief model (HBM) was used for this research. Data was collected from a sample of 444 adult individuals split across Morocco (n = 215) and India (n = 229). Data analysis was carried out using two-stage multiple-analytic techniques. First, structural equation modeling (SEM) was employed to test the hypothesized relationships. Second, an artificial neural network (ANN) model was employed to rank the significant independent variables obtained from SEM analysis. The results of SEM showed that perceived benefit is the key predictor of the protective behavior in Morocco, followed by self-efficacy, and then perceived severity. By contrast, ANN analysis showed that perceived severity was the most vital factor for predicting the protective behavior in Morocco, followed by perceived benefits, and then self-efficacy. For the Indian sample, both SEM analysis and the ANN model revealed that the impact of perceived susceptibility on the adoption of the protective measure is stronger than that of cues to action. Theoretical contributions and managerial implications are also discussed toward the end.

1. Introduction

The coronavirus disease 2019, commonly known as COVID-19, is a zoonotic disease, transmitted initially from animals to humans and caused by the virus SARS-CoV-2 (WHO, 2020a, 2020b). The person-to-person COVID-19 transmission occurs directly through coughing or sneezing and indirectly through contaminated surfaces or objects (WHO, 2020c). As of December 31, 2019, the first case of COVID-19 in the world was reported (WHO, 2020d). The outbreak rapidly propagated around the world and was declared on the 30th of January of 2020 as an international public health threat, by which time the vaccine against COVID-19 was unavailable (WHO, 2020e). Accordingly, the adoption of health measures was widely recommended by the WHO to control the global pandemic (WHO, 2020f).

A thorough analysis of the scientific literature suggests that health-protective behaviors against respiratory infections encompass three different types: (1) preventive behaviors such as hand-washing, mask-wearing, and vaccine uptake, (2) avoidant behaviors such as social distancing and avoidance of crowds, and (3) management of illness behaviors such as taking antiviral medications (Gutiérrez-Doña et al., 2012; Karademas et al., 2013; Kim et al., 2015; Wang et al., 2016). An examination of existing works also reveals that considerable effort has been invested to further the current knowledge on the behavioral determinants that influence adherence to protective measures. In particular, perceived benefits (Liao et al., 2011a; Gaygısız et al., 2012), anticipated regret (Liao et al., 2011b; Pentea et al., 2020), knowledge (Liao et al., 2011a; Zottarelli et al., 2012), self-efficacy (Payaprom et al., 2011; Prue et al., 2019), subjective norm (Yardley et al., 2011; Ng et al., 2020), perceived susceptibility (Zottarelli et al., 2012; Liao et al., 2013), cues to action (Ho et al., 2013; Zhang et al., 2015), attitude (Ahmad et al., 2020; Bae and Chang, 2020), trust (Yang et al., 2014; D’Antoni et al., 2019), and perceived severity (Lee and You, 2020; Pentea et al., 2020) were among the most salient factors in shaping the adoption of health recommendations.

Extant studies have applied several social cognition models in various health-protective actions. For example, the health belief model (HBM) has been applied for explaining the antecedents of vaccine uptake (Pentea et al., 2020), hand hygiene, and social distancing (Zottarelli et al., 2012; Kim et al., 2015; Wang et al., 2016). An examination of existing works also reveals that considerable effort has been invested to further the current knowledge on the behavioral determinants that influence adherence to protective measures. In particular, perceived benefits (Liao et al., 2011a; Gaygısız et al., 2012), anticipated regret (Liao et al., 2011b; Pentea et al., 2020), knowledge (Liao et al., 2011a; Zottarelli et al., 2012), self-efficacy (Payaprom et al., 2011; Prue et al., 2019), subjective norm (Yardley et al., 2011; Ng et al., 2020), perceived susceptibility (Zottarelli et al., 2012; Liao et al., 2013), cues to action (Ho et al., 2013; Zhang et al., 2015), attitude (Ahmad et al., 2020; Bae and Chang, 2020), trust (Yang et al., 2014; D’Antoni et al., 2019), and perceived severity (Lee and You, 2020; Pentea et al., 2020) were among the most salient factors in shaping the adoption of health recommendations.

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et al., 2012). The existing empirical studies are focused on explaining the compliance with health preventive measures in the context of a variety of respiratory infectious diseases such as seasonal flu (Yardley et al., 2011), MERS (Yoo et al., 2016), H1N1 (Payaprom et al., 2011), H5N1 (Liao et al., 2011a), and COVID-19 (Ahmad et al., 2020).

Although findings from the existing empirical studies may provide valuable insights to manage future respiratory epidemics, these studies also show some boundaries. First, most studies of behavioral response to infectious disease were conducted in a single country, including Germany (Reuter and Renner, 2011), Thailand (Payaprom et al., 2011), the United States (Zottarelli et al., 2012), Hong Kong (Liao et al., 2011a), and the United Kingdom (Yardley et al., 2011). Yet, examining the determinants of health behaviors on a multi-country level remains limited. To our knowledge, no study has compared how the determinants of health-related behaviors can differ in the context of Morocco and India. Thus, the first aim of this study was to compare the adoption of avoidant protective measures among Moroccan and Indian adults. Second, some studies have used only one single data analysis tool to validate the hypothesized models. These include, for example, structural equation modeling (Liao et al., 2013; Yoo et al., 2016; Ng et al., 2020) or multiple regression analysis (Wang et al., 2016; D’Antoni et al., 2019; Penţa et al., 2020). This is problematic because these studies might not assess non-linear associations between preventive measures adoption and predictor constructs. To our knowledge, there have been relatively few attempts in behavioral medicine literature to use a two-stage multi-analytical approach combining SEM with ANN. Hence, the second aim of this study is to apply a two-staged SEM and ANN modeling technique to examine both linear and non-linear relationships among HBM variables.

The rest of this study is arranged as follows. Section 2 provides a brief overview of the HBM and a review of existing studies on health preventive behaviors. Section 3 presents the theoretical framework and develops the research hypothesis. Section 4 explains the data collection procedure, describes the study instruments, and illustrates the two-stage SEM-ANN approach. Section 5 outlines the characteristics of respondents and reports the outcomes of SEM-ANN modeling. Section 6 outlines a discussion of the results, reports the implications of the research findings, elucidates the boundaries of this study, and suggests directions for future research. Section 7 concludes this study by summarizing the results.

### 2. Theoretical background and related work

In recent years, investigating the determinants of health-related behaviors during the outbreak of infectious respiratory diseases has been the focus of the scientific literature in behavioral medicine (Gutiérrez-Dona et al., 2012; Zottarelli et al., 2012). A variety of health behavior theories have been widely tested to investigate the essential elements affecting the behavioral response to health-protective actions. Prominent among these precautionary measures are vaccination uptake (Liao et al., 2011b), covering mouth when sneezing (Liao et al., 2011a), hand hygiene (Reuter and Renner, 2011), home confinement (Teasdale et al., 2012), mask-wearing (Yoo et al., 2016), participating in sports activities (Chirico et al., 2020), and safer traveling (Han et al., 2020). In this work, the HBM has been adopted as the conceptual framework to examine the determinants leading to the adoption of health behaviors in the context of the COVID-19 pandemic in two countries (i.e., Morocco and India). HBM is one of the most popular frameworks in predicting health-related behavior (Penţa et al., 2020). This belief-based model postulates that health prevention behaviors are predicted by six behavioral determinants: perceived susceptibility, perceived severity, perceived benefits, perceived barriers, cues to action, and self-efficacy (Rosenstock et al., 1988). HBM has been used to examine health-related behavior in various infectious respiratory epidemics (Zottarelli et al., 2012; Bae and Chang, 2020; Penţa et al., 2020).

In a longitudinal study, Penţa et al. (2020) extended the applicability of the HBM to understand factors that predict vaccination intention among 401 young adults in Romania. Results suggested that anticipated regret, perceived benefits, and perceived susceptibility to being affected by seasonal flu were positively and significantly associated with the individuals’ intention to vaccine against seasonal flu. They also demonstrated that the modified HBM explained 60% of the variance in vaccination intention. A cross-sectional study carried out during the 2009 H1N1 outbreak in the United States includes past behavior and knowledge in the HBM (Zottarelli et al., 2012). Data collected from 909 students showed that knowledge, perceived susceptibility, past behavior, and perceived threat were all significant determinants of the student’s adherence to non-pharmaceutical interventions. The study also concluded that the extended version of HBM predicts over 17% of behavior-related preventive measures. In the context of COVID-19 in South Korea, an empirical research by Bae and Chang (2020) draws inspiration from the HBM in conjunction with supplemental factors of the TPB such as attitude, subjective norm, and perceived behavioral control. By applying the SEM approach the authors affirmed that perceived susceptibility is a fundamental variable in boosting subjective norm and intention towards untact tourism. Findings of this study also evinced that worry has a significant impact in the development of attitude towards untact tourism.

### 3. Research model and hypotheses development

The theoretical framework of this study is derived from the HBM (Rosenstock et al., 1988) and it consists of six latent variables. More specifically, perceived severity, perceived susceptibility, perceived benefits, cues to action, and self-efficacy were used as the exogenous constructs in the structural model. On the other hand, avoidant protective behavior was treated as the only endogenous construct in this model. For simplicity, the five hypothetical relationships between dependent and independent latent variables of the research model are represented visually in Fig. 1.

#### 3.1. Perceived severity

Perceived severity is often described as the individual’s subjective assessment of the seriousness of a given illness (Penţa et al., 2020). The idea that the perceived severity of the disease has a positive impact on determining the preventive measures during pandemics has received repeated support from extant empirical studies. For example, Lee and You (2020) evaluated a health behavior model to predict which factors drive the adoption of preventative actions in South Korea. Results from multivariate linear regression revealed that perceived severity was linked to higher intention to engage in protective behaviors during the
COVID-19 pandemic. Prue et al. (2019) in their work demonstrated that individuals with a high belief in the seriousness of the Ebola virus are more likely to comply with the protective recommended behaviors in the United States. However, a study conducted by Gaygısız et al. (2012) in Turkey suggests that the individuals’ perception of possible negative consequences of H1N1 was positively but non-significantly associated with carrying out health-protective measures against the disease. Karadem et al. (2013) also concluded that the individual’s belief in the severity of H1N1 influenza is a positive but not significant predictor of performing the protective health behaviors in Greece. Thereby, the above inconsistency in the existing empirical evidence led the present study to hypothesize that:

**H1.** Perceived severity will have a significant and positive impact on the adoption of protective behavior.

### 3.2. Perceived susceptibility

Perceived susceptibility is defined as the extent to which an individual estimates the likelihood and chance of becoming infected with the disease (Ng et al., 2020). The literature related to respiratory infectious disease has suggested that individuals are more likely to comply with health-recommended actions if they feel personally vulnerable to the illness. A survey of individuals in the United States investigating peoples’ adoption of protective behaviors indicated that perceived susceptibility was an important factor in predicting health-protective decisions against H1N1 influenza (Zottarelli et al., 2012). Moreover, Liao et al. (2013) reported that the person’s perception of the likelihood of getting H1N1 affects positively and significantly the adoption of recommended preventive measures among the adult population in China. Similarly, Wang et al. (2016) suggested that beliefs about the subjective probability of contracting H7N9 infection were positively and significantly related to recommended behaviors against the illness. However, Lee and You (2020) founded in their empirical study within South Korean respondents, that perceived susceptibility to COVID-19 was not significantly associated with hand hygiene, mask wearing, and social distancing practices. Hence, the contradictory results in the literature mentioned above leads to propose the following hypothesis for investigation:

**H2.** Perceived susceptibility will have a significant and positive impact on the adoption of protective behavior.

### 3.3. Perceived benefits

Perceived benefits refer to the degree to which individuals believe that adopting the recommended preventive measures will protect them from contracting the illness (D’Antoni et al., 2019). Scholars in psychological responses to infectious disease suggest that perceived benefits to be a crucial predictive element of preventive measures adherence. For instance, Liao et al. (2011a) revealed that in addition to the relationship between H5N1-related knowledge about the disease and the adoption of the recommended protective behaviors, beliefs about the benefits of prevention actions increase individual’s adherence to preventive recommendations against H5N1 influenza. Moreover, an investigation conducted by Gaygısız et al. (2012) across Turkey in the context of the H1N1 influenza pandemic concluded that adherence to preventive measures was influenced by the positive consequences of the recommended protective behavior. Panja et al. (2020) examined the determinants of vaccination in the influenza virus outbreak in Romania. Results suggested that perceptions of benefits alongside the anticipated regret were significant determinants of the likelihood of protective behavior. In contrast, findings from a recent study conducted by Harris and Armien (2020) in a national sample from Panama indicated that the individual’s beliefs in the effectiveness of the health recommendation were positively but non-significantly associated with adopting preventive measures. To further explore these contradictions in past studies, the current research hypothesizes that:

**H3.** Perceived benefits will have a significant and positive impact on the adoption of protective behavior.

### 3.4. Cues to action

Cues to action refer to formal or informal health education that might trigger carrying out preventive measures, such as exposure to information obtained from traditional media, social media, or health-related communication with friends, family, doctors, and coworkers (Ho, Li and Cao, 2019). The construct of cues to action has been demonstrated to be an important determinant of health-protective actions in a health emergency. According to a study developed in the context of the H1N1 epidemic in Singapore (Ho et al., 2013), a higher level of interpersonal discussion on H1N1 triggers more adoption of recommended preventive measures. Similarly, Zhang et al. (2015) assume a positive association between cues to action and protective behaviors against infectious diseases. These authors suggest that exposure to prevention information against H1N1 on mass media leads college students in the United States to undertake precautionary behaviors. Along this line, Yoo et al. (2016) showed that receiving information from social network sites that promote awareness about the MERS infectious disease enhances the individual’s intention to comply with handwashing and mask-wearing practices in South Korea. However, Harris and Armien (2020) recently indicated that exposure to messages from physicians, government, and leaders was positively but non-significantly associated with the adherence to prevention measures in Panama. The above divergence among previous work leads to the following assumption:

**H4.** Cues to action will have a significant and positive impact on the adoption of protective behavior.

### 3.5. Self-efficacy

Self-efficacy is defined as the individuals’ confidence in their ability to perform the required preventive health measures against a particular illness (Prue et al., 2019). Recent work on health decision-making related to respiratory pandemics indicates self-efficacy as a necessary precursor of protective behaviors. In the context of the H1N1 outbreak, Payaprom et al. (2011), for example, attempted to predict vaccination uptake and revealed that individuals’ confidence in their ability to successfully perform the preventive measure is positively associated with the behavioral response to public health recommendation in Thailand. Likewise, Wang et al. (2016) have investigated several antecedents that influence health-protective decisions in response to H7N9 Influenza. Based on data collected from 762 Chinese adults, they propose that self-efficacy is among the prominent factors that encourage increased individuals’ compliance with precautionary behaviors. Moreover, Prue et al. (2019) argued that if travelers in the United States believe that they could perform preventive behaviors, then they will be more likely to comply with protective action recommendations taken by the public authorities. More recently, Ng et al. (2020) assumed that when healthcare workers in Hong Kong believe that they can successfully execute a recommended action, a high degree of adherence to preventive recommendations will be generated. Consistent with the evidence described below, the following is postulated:

**H5.** Self-efficacy will have a significant and positive impact on the adoption of protective behavior.

### 4. Material and methods

#### 4.1. Participants and procedure

A cross-sectional online survey was used for data collection in the
period between May 08, 2020, and June 26, 2020. During this period, an e-mail invitation was sent to English-speaking, Arabic-speaking, and French-speaking adults who reside in Morocco and India. The rationale of selecting participants from Morocco and India is to assess the individual’s beliefs and protective health behaviors during the COVID-19 pandemic across two culturally different countries (see Fig. 2). Participation was voluntary and those who responded to the survey received the results of the study at their email address. About 1000 completed the online survey and 444 valid observations were used for data analysis after exclusion of incomplete answers and non-serious responses.

Before the main data collection, an academic researcher in neuroscience was requested to review the wording of each item and the format of the questionnaire to ensure content validity. Also, a pretest was conducted among a sample of 100 individuals. As a result, the wording of questionnaire measures and response scales has been refined according to the comments and feedback of the expert and respondents. Furthermore, reliability and validity tests were performed for each construct. Following the results, six poor measures have been excluded from the initial measurement model.

The final online survey contains four sections. The first section consisted of a filter question asking participants whether they were above 18 years of age. Only those who had answered affirmatively were conducted in the next section. The second section comprised of an informed consent explaining the purpose of the study, the procedures to be followed, and the risks and benefits that can be expected of taking part in the survey. At this point, participants were made aware that they free to withdraw from the survey at any time and that all the data will be completely stored and analyzed anonymously. The third section measures the health belief model’s constructs. Finally, the fourth section captures the respondents’ characteristics such as gender, age, level of education, health status, etc.

4.2. Measures

The reflective indicators were based on validated measures from prior empirical studies in the context of MERS and H1N1 influenza outbreaks and were adjusted to fit the context of the COVID-19 pandemic. Perceived severity of COVID-19 consists of two items on a 5-point Likert scale that going from strongly disagree (1) to strongly agree (5). Manifest variables were adopted from the study conducted by Yoo et al. (2016). Perceived susceptibility to COVID-19 was measured with two items on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5). Observation variables were derived from the study conducted by Yoo et al. (2016). The construct of perceived benefits was captured by three items on a 5-point Likert scale going from no attention (1) to very close attention (5). Measures of self-efficacy of protective behavior was measured with two items on a 5-point Likert scale going from strongly disagree (1) to strongly agree (5). Indicator variables were drawn from those proposed by Yang et al. (2014). At long last, avoidant protective behavior was measured using a single item (i.e., avoiding crowds during the COVID-19 outbreak) on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5). Item measurements were based on the work of Kim et al. (2015).

4.3. SEM-ANN approach

Inspired by how the neurons of the human brain are interconnected, the artificial neural network (ANN) is capable of (1) acquiring knowledge through learning (training), and (2) storing that knowledge through interneuron connection strengths (Haykin, 2009). The architecture of a multi-layer ANN operates as follows: three types of layers, namely, input, hidden, and output layers constitute the ANN model. Each layer is made up of artificial neurons called nodes or units (Alam et al., 2020). Every input node has a corresponding synaptic weight of its own that is transferred to all hidden nodes through synaptic links. The hidden nodes then convert the weighted sum of the inputs to some output values with the help of an activation function (Haykin, 2009).

In the present study, the model was empirically analyzed using a combination of two techniques: structural equation modeling (SEM) and ANN. SEM is suitable for testing the hypothesized relationships and determining the significant antecedent of the dependant constructs (Hair et al., 2018). One key advantage of using such a model is that besides assessing the measurement relationships between observed and latent variables, it can also help to examine the structural relationships linking the exogenous and endogenous latent variables (Hair et al., 2018). Furthermore, SEM has been widely used in prior research on behavioral medicine, particularly in empirical studies about health-protective behaviors that limit the spread of respiratory infection diseases (Liao et al., 2011b; Gutierrez-Dona et al., 2012; Teasdale et al., 2012; Ho et al., 2013). Nevertheless, this multivariate technique only can analyze linear associations between endogenous and exogenous variables (Hair et al., 2018). On the other hand, the neural network technique allows us to use linear as well as nonlinear causal relationships between behavioral predictors and the dependant constructs (Haykin, 2009). However, ANN is not suitable for theory testing as it is based on the “black-box” mechanism (IBM SPSS, 2012). Furthermore, it is often difficult for the neural nets to assess the reliability and validity of the constructs. Therefore, to complement each other, a two-stage multi-analytical approach combining SEM with ANN was adopted within the two country datasets of the present study (i.e., Morocco and India).

At the primary stage, this research study employed a two-step SEM approach in AMOS 24 to analyze the proposed framework as recommended by Hair et al. (2018). Specifically, the measurement model (CFA model or outer model) was first evaluated, and the structural model (inner model) was then assessed. In the second stage of SEM-ANN analysis, this research applied an ANN technique in IBM SPSS 21 to identify the relative importance of each significant variable obtained by SEM in predicting the avoidant protective behavior (IBM SPSS, 2012).

5. Results

5.1. Characteristics of participants

The socio-demographic characteristics of the two subsamples can be found in Table 1. A total of 444 participants were included in the study, 51.6% of them were Indians (n = 229) and 48.4% were Moroccans (n = 215). The majority of the participants were from an urban area (89.9%) and single (85.1%). The gender distribution was almost balanced: 46.8% were women (n = 208) and 53.2% were men (n = 236). More than half of the participants were aged 18–24 years (61.5%) and lived with 4–6 people in the same household (59.7%). Approximately half of the participants were students (49.5%) with a Master’s degree (43.5%). Also,

![Fig. 2. Hofstede cultural differences across Morocco and India (Source: www.hofstede-insights.com).](image-url)
5.2. Measurement model

According to Hair et al. (2018), the assessment of the measurement model depends on three conditions (1) testing the measurement model fitness, (2) examining the constructs’ reliability, and (3) evaluating the constructs’ validity.

According to the results, the measurement model indices provided an acceptable fit of the data for the whole sample, the Moroccan sample, and the Indian sample. As the measurement model used in the study achieved adequate fit indices, the reliability and validity of the constructs should be examined (Hair et al., 2018).

5.2.1. Reliability analysis

The constructs’ reliability is examined using three criteria: First, evaluating the composite reliability (CR) of each construct. Second, assessing the values of Cronbach’s alpha. Third, evaluating the average variance extracted (AVE) estimates. The reliability values for Cronbach’s α, CR, and AVE are presented in Table 3.

As shown in Table 3, CR takes a range of values from 0.70 to 0.84 for the full sample, from 0.72 to 0.84 for the Moroccan sample, and from 0.73 to 0.81 for the Indian sample. According to Hair et al. (2018), the minimum recommended reliability values range from 0.60 to 0.70. Thus, the CR of each construct is achieved. Furthermore, the values of coefficient alpha range from 0.72 to 0.81 for the full sample, from 0.71 to 0.84 for the Moroccan sample, and from 0.70 to 0.83 for the Indian sample. That means Cronbach’s α for the six latent variables is either equal to or higher than 0.70 which exceeds the lower limit of acceptability (from 0.60 to 0.70) as advocated by Hair et al. (2018). The values associated with AVE ranged from 0.54 to 0.69 for the full sample, from 0.53 to 0.73 for the Moroccan sample, and from 0.57 to 0.68 for the Indian sample. All AVE exceed the 50 percent rule of thumb. Therefore, the measured indicators of the study are highly interrelated with their respective latent variables, providing evidence of constructs’ reliability.

5.2.2. Validity analysis

To assess the validity of unobserved latent constructs, both convergent and discriminant validity were checked in the current research. As seen in Fig. 3, the factor loadings of all un-removable items range from 0.74 to 0.90 for the full sample, from 0.71 to 0.94 for the Moroccan sample, and from 0.71 to 0.90 for the Indian sample. Thus, according to Hair et al. (2018), all factor loadings of the study are higher than the 0.70 rule of thumb. Moreover, the results suggest that all standardized loading estimates of each observed variable are statistically significant at the 0.001 level as recommended by Hair et al. (2018). The convergent validity of the measurement model for the full sample, the Moroccan, and Indian samples is achieved. Concerning the discriminant validity, the inter-correlation matrix in Table 3 shows that the square root of the AVE of each latent variable (bold diagonal values) was equal to or higher than 0.70 which exceeds the lower limit of 0.55 which exceeds the lower limit as advocated by Hair et al. (2018). Thus, the convergent validity of the measurement model for the full sample, the Moroccan, and Indian samples is achieved. Concerning the discriminant validity, the inter-correlation matrix in Table 3 shows that the square root of the AVE of each latent variable (bold diagonal values) was equal to or higher than 0.70 which exceeds the lower limit of 0.55 as advocated by Hair et al. (2018).

5.3. SEM outcomes

Fig. 3 and Table 4 presents the SEM analyses for all hypothesized paths. Based on the maximum likelihood estimation (MLE), all the direct hypotheses are supported in the full sample, three out of five direct hypotheses (H1, H3, and H5) are supported in the Moroccan sample, while only two out of five direct hypotheses (H2 and H4) are confirmed in the Indian sample. More specifically, perception in the seriousness of COVID-19 was significantly associated with greater compliance with protective measure for Moroccan respondents (H1: β = 0.183; t = 2.413; p < 0.05) but not for Indian respondents (H1: β = 0.100; t = 1.103; p > 0.05). Moreover, perceived susceptibility to COVID-19 was significantly associated with the adoption of the protective avoidant behavior in India (H2: β = 0.269; t = 3.446; p < 0.001) but not for the Moroccan sample.
and predict the neural network model as can be seen in Fig. 4, Fig. 5, and Fig. 6. Similar to a previous study by Chong (2013), the significant results in SEM analysis (see Table 4) were given as inputs in the three ANN models to overcome the overfitting of the ANN. Specifically, the ANN model of the full sample has five input nodes (perceived severity, perceived susceptibility, perceived benefits, cues to action, and self-efficacy). The ANN model of the Moroccan sample comprises three input nodes (perceived severity, perceived benefits, and self-efficacy). The ANN model of the Indian sample has two input nodes (perceived susceptibility and cues to action). As stated by Chong (2013), the output layer consisting of one output node for the three ANN models was represented by the dependent variable namely avoidant health behavior.

The three neural network models considered in the present study have the approach by Talukder et al. (2020), this research used seventy percent of data sets to train the NN model and thirty percent of data sets for testing. Similar to the approach by Talukder et al. (2020), this research used seventy percent of data sets to train the NN model and thirty percent of data sets for testing.

5.4. ANN results

Following the suggestions by Alam et al. (2020), a multi-layer perceptron (MLP) method was employed in the present research to train and predict the neural network model as can be seen in Fig. 4, Fig. 5, and Fig. 6. Similar to a previous study by Chong (2013), the significant results in SEM analysis (see Table 4) were given as inputs in the three ANN models to overcome the overfitting of the ANN. Specifically, the ANN model of the full sample has five input nodes (perceived severity, perceived susceptibility, perceived benefits, cues to action, and self-efficacy). The ANN model of the Moroccan sample comprises three input nodes (perceived severity, perceived benefits, and self-efficacy). The ANN model of the Indian sample has two input nodes (perceived susceptibility and cues to action). As stated by Chong (2013), the output layer consisting of one output node for the three ANN models was represented by the dependent variable namely avoidant health behavior.

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5.4.1. Validation of ANN

Table 5 summarizes the results of the neural network validation for the full sample, the Moroccan sample, and the Indian sample. Similar to the approach by Talukder et al. (2020), this research used seventy percent of data sets to train the NN model and thirty percent of data sets for testing the trained NN model. In this study, the sigmoid function was applied as the activation function associated with both the hidden layer and output layer of the ANN (Liéban-Cabanillas et al., 2018). To measure the accuracy of the ANN model, the Root Mean Square Error (RMSE) is computed using the formula $\text{RMSE} = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n}}$, where $\text{MSE}$ is the mean square of errors, $\text{SSE}$ is the sum square of errors, and $n$ refers to the number of data points.
to the sample size for both training and testing data points. To properly address the ANN overfitting issue, the RMSE values were obtained from a 10-fold cross-validation procedure (Liíbana-Cabanillas et al., 2018). Following the suggestions by Chong (2013), a number of hidden nodes varying from 1 to 10 was used to examine the neural networks. In the training model, the average RMSE values for the full sample was 0.105, for the Moroccan sample was 0.110, while for the Indian sample was 0.152. In the testing model, the mean values for RMSE for the full sample was 0.103, for the Moroccan sample was 0.110, while for the Indian sample was 0.159. Therefore, it can be concluded that the ANN employed in the present study has a high predictive precision since the RMSE values of the three samples were quite small.

To gain more insights, the coefficient of determination ($R^2$) was then calculated by using the formula $R^2 = 1 - \frac{\text{SSE}}{\text{SST}}$. Hence, the ANN developed in this research has been able to predict approximately a variance of 93%, 86.1%, and 91.3% in avoidant protective behavior for the full sample, Moroccan sample, and the Indian sample, respectively.

### 5.4.2. Sensitivity analysis

The results of the sensitivity analysis for the three samples are displayed in Table 6. The purpose of performing a sensitivity analysis was to identify the most important input variables in predicting the output variable. The normalized importance, which is presented as percentages, is the ratio of the average importance of each independent variable to the highest importance value of the predictor (IBM SPSS, 2012). In this study, the sensitivity for the full sample was found to be 100% for perceived benefits, 79% for self-efficacy, 74% for perceived susceptibility, 59% for perceived severity, and 50% for cues to action. For the Moroccan sample, sensitivity was found to be 100% for perceived severity, 99% perceived benefits, and 51% self-efficacy. For the Indian sample, sensitivity was found to be 100% for perceived susceptibility and 79% for cues to action (see Table 6).

A comparison between the findings obtained from ANN-based models and SEM is presented in Table 7. For the Moroccan sample, the order of path coefficient from SEM is not the same as the order of normalized importance obtained from the neural network. More specifically, the findings from the neural network model showed that perceived severity (NI = 100%) was the most important predictor of the avoidant protective behavior in Morocco, followed by perceived benefits (NI = 99%), and then self-efficacy (NI = 51%). In contrast, SEM results evidenced that perceived benefits ($β = 0.253$) is the strongest predictor of the adoption of the avoidant protective measure in Morocco, followed by self-efficacy ($β = 0.193$), and then perceived severity ($β = 0.183$). A possible reason behind this difference in the ranking for the Moroccan sample is that ANN can capture linear as well as nonlinear associations between perceived severity, perceived benefits, self-efficacy, and avoidant protective behavior. For the Indian sample, there is no change in the relative importance ranking of the independent variables between SEM and ANN results. Specifically, the NN-sensitivity analysis demonstrated that perceived susceptibility (NI = 100%) is the most influential determinant of the adherence to protective actions in India followed by cues to action (NI = 79%). Similarly, SEM analysis revealed that the adoption of the protective measure in India was most influenced by perceived susceptibility ($β = 0.269$) followed by cues to action ($β = 0.162$). Therefore, the key antecedents obtained from SEM results for the Indian sample are supported by the ANN model results.

### 6. Discussion

In this study, the percentage of variance in ANN was 93% for the full sample, 86.1% for the Moroccan sample, and 91.3% for the Indian sample. On the other hand, the percentage of variance in SEM was 33.1%, 31.1%, and 36.1% for the full sample, Moroccan sample, and the Indian sample, respectively. Therefore, the ANN performed better than SEM models with respect to the prediction of avoidant protective behavior. As a result, the findings from ANN sensitivity analysis
presented in Table 7 were used instead of the findings obtained by SEM to conclude the final ranking among the adoption factors.

6.1. Major findings in Morocco

As expected, the ANN results showed that perception of the COVID-19 severity is the most important factor with a significant positive effect on the adoption of protective behavior among Moroccan residents. This is consistent with the findings of studies conducted in the United States and South Korea that support the strong influence of perceived severity on the behavioral responses to health-related recommendations (Prue et al., 2019; Lee and You, 2020). In Morocco, this may imply that the greater individual’s assessment of the negative consequences of COVID-19 such as death, leads to a higher level of compliance with the health-protective measures.

Furthermore, the finding of the present study revealed that COVID-19 infection-likelihood perception was not related to compliance with the health preventive measure in Morocco. This is in line with the finding of Lee and You (2020) who claimed that perceived susceptibility is not significant in determining the adherence to health practices in South Korea. However, this is in sharp contrast with studies set in China by Liao et al. (2013) and Wang et al. (2016), which identified a significant relationship between beliefs about the likelihood of infection and compliance with the protective measures. With 81.9% of the respondents reported that their health condition is good or very good, it is understandable that Moroccan people might do not believe that the chance of contracting the COVID-19 for oneself and the people around them will motivate them to avoid crowds during the COVID-19 outbreak.

In line with findings from the study in Hong Kong by Liao et al. (2011a) and the study in Romania by Penta et al. (2020), the perceived benefits of the preventive measure was the second major factor with a
significant positive impact on the adherence to avoidant protective actions in Morocco. A plausible explanation could be that Moroccan individuals may avoid crowds during the COVID-19 pandemic because they believe in the effectiveness of the recommended protective behavior to help protect themselves, neighbors, family, and friends against the COVID-19.

Also, self-efficacy was the third strongest predictor after perceived severity and perceived benefits for Moroccan individuals. This finding is in agreement with the empirical evidence, showing that adherence to preventive measures in Thailand and China is significantly enhanced by self-efficacy (Payaprom et al., 2011; Wang et al., 2016). This may further suggest that Moroccan respondents who believe subjectively that they had the ability to adopt the preventive behaviors against COVID-19 will avoid crowds during the COVID-19 pandemic.

Surprisingly, an unexpected result in the current study confirmed that the construct of cues to action has an insignificant impact on the decision to avoid crowds during the COVID-19 pandemic in Morocco. Evidence in support of this non-significant relationship between cues to action and protective behavior can be found in a study conducted in Panama by Harris and Armién (2020). It is possible that although health information on COVID-19 was received ubiquitous coverage in mass media and social media, the attention to these external stimuli may have nothing to do with the adoption of the protective measure among the Moroccan participants in this study.

6.2. Major findings in India

The results of this research showed that adherence to avoidant protective behavior in India is not significantly predicted by the perceived severity of COVID-19. This finding concurs with the studies carried out by Gaygısız et al. (2012) and Karademas et al. (2013), which have also established a non-significant relationship between perceived severity and compliance with the health preventive measures in Turkey and Greece. As the present study was conducted in the early phase of the COVID-19 pandemic, one possibility is that even if 79.5% of the Indian participants were university degree holders, they may not have prior knowledge about the ways of handling this new disease. As a result, regardless of how they believe that the COVID-19 to be deadly this may not be necessarily important to comply with the protective measures.

Similarly, the compliance with recommended protection measures was not significantly influenced by the perceived benefits, which is in line with a previous study by Harris and Armién (2020), who found that perceived benefits and the adherence with recommended protective actions in Panama were not significantly related. One explanation for this insignificant relationship is that Indian individuals may have not prior experience with the adoption of the protective measure, and thus they are not familiar with the perceived effectiveness of such health recommendations to protect them from getting the COVID-19.

Moreover, this study found that self-efficacy does not encourage Indian individuals to comply with protective action recommendations in the case of the COVID-19 pandemic. The present finding is not consistent with studies set in Thailand, the United States, and Hong Kong which reported that the individual’s self-efficacy is a significant antecedent of compliance with recommended behaviors (Payaprom et al., 2011; Prue et al., 2019; Ng et al., 2020). It may be that a higher increase in an individual’s ability to avoid crowds in India does not necessarily lead to greater adoption of preventive health actions against the COVID-19.
The findings of this study have many valuable contributions for scholars working on studies related to behavioral medicine, especially those explaining behavioral responses to infectious disease. More specifically, the current research can serve as a baseline for understanding the reasons that motivate people to engage in preventative measures during the COVID-19 pandemic. The results of this study demonstrated the validity of the HBM constructs in two countries with different cultural dimensions proposed by Hofstede’s findings. Therefore, by showing variation in protective measures adherence at a multi-country level, this study adds more knowledge regarding cultural differences within Moroccan and Indian settings. To follow on, SEM-ANN modeling is a relatively new approach in the context of health measures adoption. From a methodological viewpoint, researchers in this field can use this multi-analytical technique to obtain good prediction accuracy and enhanced theory testing. Lastly, the findings of this research confirm previous infectious disease studies by showing the importance of including perceived severity, perceived benefits, self-efficacy, perceived susceptibility, and cues to action as the key components of preventive measures adherence.

### 6.4. Implications for practice

From a practical perspective, the current study provides several useful health communication strategies for the stakeholders involved in containing and managing future infectious disease pandemics. SEM-ANN analysis indicates that perceiving the COVID-19 as being severe is the most crucial determinant of the adherence to avoidant protective measures in Morocco. Therefore, creating health messages about the possible complications of the disease on the individual’s health along with highlighting the possible negative consequences of that illness on the individual’s economic situation and their social life seems to be crucial for preventing the spread of future infectious disease at a practical level. The present study also found that perceived benefit is the second important predictor of the decision to engage in health official actions in Morocco. This suggests that local health authorities should communicate continuously about the positive consequences of the protective measures during times of future pandemics, such as decreasing the chance of contracting a given illness and reducing the degree of transmission to one’s family, friends, and neighbors. Furthermore, data collected during the COVID-19 outbreak in Morocco demonstrate that self-efficacy is the third most important antecedent of behavioral compliance with protective measures. Thus, when attempting to motivate Moroccans to adopt the preventive measure in the case of future global infectious outbreaks, health risk communicators must focus on encouraging individuals to believe that they can easily perform the recommended action and should constantly provide guidance to overcome the possible drawbacks of applying that preventive health measure.

When it comes to India, the results emphasize that the individuals’ perceptions of the probability of getting COVID-19 are the most important predictor that led people to perform preventive behavior. Therefore, in the case of preparedness for future respiratory infectious diseases, it would be useful to expose credible testimony of confirmed cases to raise the individual’s awareness about the chances of becoming infected with the health threat if no preventative action was undertaken.
Finally, sensitivity analysis suggests that the attention to COVID-19-related information is the second most important factor in the adoption of protective measures in India. In this sense, the government officials in India should provide funding, infrastructure, and resources to doctors so that they can train other professionals to deliver public health recommendations over multiple channels such as traditional media (e.g., television, newspapers, radio) and Internet media (e.g., websites and social media). Such actions are necessary to raise awareness when facing future pandemic threats in India.

6.5. Limitations and future research directions

Although this study strengthens our understanding of the drivers of avoidant protective measure compliance in Morocco and India, it should be emphasized that some weaknesses need to be addressed in future research. The first limitation is the use of one single indicator to assess the avoidant protective behavior, which precludes us from checking for the construct's reliability. Although previous studies have used one single indicator in their research models (Wang et al., 2016; Yoo et al., 2016; Penja et al., 2020), it must be acknowledged that future research needs to adopt multiple observed variables to measure adequately complex concepts such as avoidance behavior. For instance, it would be useful to take into account three other measurement indicators: 1) avoidance of public transport, 2) travel avoidance, and 3) avoidance of office work. The second limitation is that this study could not make a clear distinction as to whether avoidance of crowds served as a proxy for social distancing or as a dimension of home confinement. Thus, it is of great importance for behavioral scientists to add more precision to the operationalization of the concept of home confinement to avoid potential overlapping with other constructs. The third limitation concerns the cross-sectional design of this study. As the COVID-19 situation develops over time, it may be worth noting that perceptions of individuals may also change over the different phases of the COVID-19 pandemic. Capturing changes in health beliefs at different COVID-19 pandemic phases deserve to be tested more thoroughly in future longitudinal studies. The fourth limitation is that the population representativeness may be compromised due to online surveys that were employed for data collection. Thus, it can be assumed that only well-educated individuals who have access to the Internet were able to participate in the study. To avoid selection bias, future research should also use a paper version of the survey to reach large and diverse respondents who may not have Internet access and with limited literacy. The fifth limitation is that the current study has underrepresented peoples in the 35–60 age groups (6.2%), which raises the question of the generalization of the findings to other age groups in Morocco and India. Future studies should resolve this issue by considering representative samples comprised of research subjects of different age groups. The sixth limitation is that this study was conducted on a total sample of 444 adult individuals from just two countries. Thus, the results of the present research may not be generalizable to other populations living in European or American countries for example. Accordingly, continued endeavors would be needed to replicate the finding of this study in other societies, as well as with larger sample sizes, which may be particularly important to investigate the moderating impact of culture on the adoption of precautionary measures.

7. Conclusion

The purpose of this study was to explore the behavioral determinants of the individuals’ decision to avoid crowds during the COVID-19 pandemic at a multi-country level. To meet this goal, a research framework based on HBM was empirically tested among 215 and 229 adults in Morocco and India, respectively. By using an integrative SEM-ANN approach, this research demonstrated that the perceived severity of COVID-19 is the strongest antecedent of the protective avoidant behavior in Morocco, whereas perceived susceptibility to COVID-19 contributes the most in the protective avoidant behavior in India. In light of these findings, health risk communicators should put more emphasis on such cognitive risk perceptions when tailoring health education messages to curb future infectious disease pandemics.
