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A Hybrid Model with Spherical Fuzzy-AHP, PLS-SEM and ANN to Predict Vaccination Intention against COVID-19

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Abstract: This study aims to identify the key factors affecting individuals' behavioral vaccination intention against COVID-19 in Vietnam through an online questionnaire survey. Differing from previous studies, a novel three-staged approach combining Spherical Fuzzy Analytic Hierarchy Process (SF-AHP), Partial Least Squares-Structural Equation Model (PLS-SEM), and Artificial Neural Network (ANN) is proposed. Five factors associated with individuals' behavioral vaccination intention (INT) based on 15 experts' opinions are considered in SF-AHP analysis, including Perceived Severity of COVID-19 (PSC), Perceived COVID-19 vaccines (PVC), Trust in government intervention strategies (TRS), Social Influence (SOI), and Social media (SOM). First, the results of SF-AHP indicated that all proposed factors correlate with INT. Second, the data of 474 valid respondents were collected and analyzed using PLS-SEM. The PLS-SEM results reported that INT was directly influenced by PVC and TRS. In contrast, SOI had no direct effect on INT. Further, PSC and SOM moderated the relationship between PVC, TRS and INT, respectively. The ANN was deployed to validate the previous stages and found that the best predictors of COVID-19 vaccination intention were PVC, TRS, and SOM. These results were consistent with the SF-AHP and PLS-SEM models. This research provides an innovative new approach employing quantitative and qualitative techniques to understand individuals' vaccination intention during the global pandemic. Furthermore, the proposed method can be used and expanded to assess the perceived efficacy of COVID-19 measures in other nations currently battling the COVID-19 outbreak.

Keywords: MCDM; COVID-19; Spherical Fuzzy Analytic Hierarchy Process (SF-AHP); vaccines; ANN; PLS-SEM

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1. Introduction

The World Health Organization (WHO) announced the Coronavirus Disease 2019 (COVID-19) pandemic on 11 March 2020, caused by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). As of 1 August 2021, the total number of cases recorded worldwide had reached approximately 197 million, with 4.2 million fatalities. Despite Vietnam's aggressive efforts to limit the fast spread of COVID-19, isolated cases of COVID-19 have persisted [1]. Vietnam has 215,560 illnesses as of 9 August 2021, including 2360 imported cases and 213,200 domestic cases. Given the worldwide implications of the COVID-19 pandemic on health and economics, developing efficient infection control measures to limit viral transmission is a key concern right now. As a result, vaccination is now one of the most efficient methods for building herd immunity in the population and averting a COVID-19 pandemic. In Vietnam, on 8 August 2021, the total COVID-19 vaccine administered was nearly 9,405,820 doses, of which the first dose accounted for more than 8,460,010 doses and the second dose accounted for nearly 945,810 doses [2]. Numerous

governments have enforced nationwide lockdowns and advised residents to maintain social isolation or self-quarantine. Controlling the disease's quick spread is critical as the number of affected persons continues to rise alarmingly, particularly in nations such as Italy, Hongkong, Brazil, and Korea, where circumstances threaten to spiral out of control [3–7]. Now, the COVID-19 virus has spread almost everywhere; most of the planet is in lockdown mode. It is regarded as the most severe catastrophe since the last World War [8–10]. The previous study, however, has neglected the impact of factors influencing COVID-19 preventative interventions. In fact, the solutions employed thus far are insufficient to address the COVID-19 issue, as several examples of individuals encountering serious challenges of various types have occurred. All nations require a more thorough and robust plan of action that considers the multiple criteria affected during a pandemic.

On the other hand, vaccination is regarded as the most efficient method of repelling and preventing diseases in general and the COVID-19 pandemic. However, some people are still hesitant to inject the SARS-CoV-2 vaccination for various subjective and objective reasons. Prior studies have established that vaccine rejection is a global health concern, with various possible reasons for vaccination rejection [11]. Better knowledge of vaccination and the factors that influence vaccine intention is crucial to adjust public health messages as needed in the context of the COVID-19 pandemic [12]. Some people continue to put off having injections, hesitate, or refuse to have them because they are concerned about the risks. People are usually persuaded by fear and unclear information rather than by contemplating the benefits they have obtained. Fear of vaccination presents substantial hurdles to global health prevention and protection. As a result, this study makes efforts to swiftly examine the variables that impact public views of COVID-19 vaccines and provide a more comprehensive and nuanced understanding of how these factors shape individual perspectives and behaviors.

This study ascertains the socially related factors (i.e., the COVID-19 risk perception, vaccine perception, trust in government strategy, subject norms, and social media) affecting the COVID-19 vaccination intention. In the past, few studies focused on evaluating factors of vaccination intention against COVID-19, especially investigating individuals' vaccination hesitancy and intention. Hence, the vaccination program entails various conflicting factors, including the COVID-19 risk perception, vaccine perception, trust in government intervention strategies, subject norms, and social media, all of which must be solved using Multi-Criteria Decision Making (MCDM) approaches. Several fuzzy sets have been developed over the last 60 years to cope with ambiguity, uncertainty, and difficulty in specific types of information. Mahmood et al. [13] first introduced Spherical fuzzy sets in particular as integration and synthesis of Pythagorean fuzzy sets and Neutrosophic sets to give decision-makers with a larger preference domain and allow them to express their aversion to an attribute or alternative [14]. It was evident that spherical fuzzy sets combining MCDM models under a fuzzy environment are a suitable tool to help decision-makers identify affecting factors of individuals' vaccination intention for developing comprehensive disaster preparedness and response [15].

Considering all of these points, the authors reviewed the potential applications of quantitative and qualitative methods to predict individuals' vaccination intention with the real case of Vietnam. This study aims to construct a novel three-staged model by combining Spherical Fuzzy Analytic Hierarchy Process (SF-AHP), Partial Least Squares Structural Equation Modeling (PLS-SEM) and Artificial Neural Network (ANN) to uncover crucial factors influencing intention to obtain vaccines in the COVID-19 outbreak. The following research questions have been raised:

(a) What factors influence individuals' immunization intentions against COVID-19 in the context of Vietnam?
(b) Among the significant predictors, which factor has a greater association with individuals' vaccination intention against COVID-19 in the context of Vietnam?

To fill in the research gap, a hybrid model is proposed based on valuable frameworks such as Protection Motivation Theory (PMT) for analyzing behavioral choices during

COVID-19 outbreaks that links the PVC, PSC, TRS, and SOM as well as SOI to individuals' behavioral intention to get vaccinations. Differing from the previous research, this study is the first attempt to investigate individuals' behavioral intention to get vaccinations using PMT theory, and the core determinants of PMT are examined using SF-AHP, PLS-SEM, and ANN together.

A three-step methodology is proposed with the first step of the SF-AHP [16]. AHP is one of the most popular MCDM methods [17–19], integrating with Spherical Fuzzy Sets [20], which can handle decision-making problems, vagueness and uncertainty in criteria and has the advantages of easy to use and flexibility. In this step, SF-AHP [16,21] is utilized to determine the relative weight and the importance of factors as well as eliminate the less important factors in the proposed research model. Meanwhile, it minimizes the fuzziness of 15 experts' decisions with respect to each of the factors. In the second step, PLS-SEM [22,23] analyzes the causal relationships and tests the research hypotheses. In the final step of the proposed method, ANN is deployed to predict the factors that have a greater association with vaccination intention against COVID-19 in Vietnam.

Our approach has several advantages over the existing multivariate regression approach as follows:

(1) This study is first to propose a hybrid three-staged model combining SF-AHP, PLS-SEM and ANN to analyze individuals' behavioral intention to vaccinate.
(2) The SF-AHP can identify the significant factors of individuals' vaccination intention through relative weights based on experts' opinion. PLS-SEM can deploy the results of SF-AHP to conduct the massive survey to collect larger sample.
(3) The ANN model can detect both linear and nonlinear models and compensatory and non-compensatory models, and it can learn from deep learning training sessions. Because it employs a feed-forward-back-propagation (FFBP) algorithm, ANN is a subset of machine learning (ML). Thus, by combining the strengths of SF-AHP, PLS-SEM, and ANN, we can complement and leverage the strengths of both methods, advancing the expert systems and artificial intelligence methodologies.
(4) The benefits of this research will accrue to individuals, ministries of health, and educational institutions through the provision of broad knowledge, as the results are expected to identify the factors influencing vaccination intention among Vietnamese. Understanding these factors would enable the government to optimize its intervention strategies and accelerate the massive vaccination campaigns against COVID-19.

This study is organized as follows: Section 2 describes the background of the literature and hypotheses. Section 3 addresses the research methodology, including detailed SF-AHP, PLS-SEM, and ANN approaches. In Section 4, case study analysis and results are presented. Discussions are provided in Section 5. Finally, Section 6 concludes the findings and suggests implications and future work with results.

2. Literature Review

The worldwide crisis of economic and public health has been derived by COVID-19 pandemic. Most governments have applied numerous efforts to control and tackle with the disease transition such as lockdowns, curfews and common health testing as well as vaccination and so on [24]. Among governmental interventions, vaccination plays a significant role in the prevention of many infectious diseases and reduces the huge impact of the current COVID-19 pandemic. However, vaccination programs have encountered multiple challenges because of vaccine hesitancy and refusing vaccination uptake [25]. This means that the pandemic control needs to reach herd immunity. From existing literature review, a number of mathematical and statistical models have been constructed to conduct a critical analysis of the continuing COVID-19 and other related disease outbreaks [26–28]. Alyasseri et al. [26] conducted a thorough assessment of prior research that used deep learning (DL) and machine learning (ML) approaches to provide quick and accurate COVID-19 diagnosis in the healthcare sector, and their findings revealed that ANN was

the most commonly used DL mechanism. Sabzi et al. [27] also proposed that time series forecasting models be used with the MCDM model to offer more dependable and accurate predictions. Also, Fei et al. [28] demonstrated how ML and DL approaches might be used to address healthcare issues during the COVID-19 pandemic. Furthermore, it is critical to recognize the many epidemiological contributions to forecasting the virus's trajectories [29]. Vaccination uptake varies between individuals, and there may be variances in the variables that influence behavioral intention to get vaccinated. To have a better understanding of all the factors of immunization uptake, several approaches have been conducted to investigate the preventive health behaviour. Using a novel integration of three methodologies, MCDM, PLS-SEM, and machine learning-based ANN, this work, unlike any previous works, seeks to demonstrate how individuals want to get vaccinated based on Protection Motivation Theory (PMT) and Theory of Planned Behaviour (TPB). Theoretical background and hypothesis development will be presented in detail in the following sections.

2.1. Theoretical Foundation

Adopting protective behaviors in response to infectious respiratory illnesses such as hand cleanliness, social distance, and mask-wearing can significantly influence the course of a pandemic. PMT [30,31] and TPB [32,33] provide valuable frameworks for analyzing behavioral choices during such outbreaks. Individuals are primarily motivated to engage in protected activity when confronted with a frightening situation. According to a prior study, people feel that engaging in preventative behavior might lessen the threat of inaction. Providing trustworthy and up-to-date information is critical during a global pandemic [34]. Currently, people may know very little about the efficacy of the COVID-19 vaccine, but negative information about vaccine side effects after vaccination is widespread on social media [35].

As a result, people's psychology is very confused and fearful, and they are debating whether or not to accept the COVID-19 vaccine [36]. Social influences show whether or not a person gets and interprets other people's opinions (especially those with close relationships, such as family members or agencies). The information and perception of COVID-19 vaccines are changing individuals' opinions about vaccination programs [37]. If individuals are aware of whether their control and abilities support their immunization against COVID-19, they have cognitive-behavioral control. The purpose of an individual to be vaccinated against COVID-19 has then been mentioned above [37–39]. Several correlational studies have examined the link between cognitive criteria and vaccination intentions [37]. Although this connection might be explained by subjective factors influencing vaccination intentions, another possibility is that people seek a specific vaccine. This is significant since it might assist them in validating their views. All factors and derived hypotheses of the extended PMT model are summarized in the following section based on the PMT from existing literature and expert opinion in the motivation to have COVID-19 vaccination.

2.2. Hypothesis Development

Perception COVID-19 Vaccine (PCV): When the COVID-19 pandemic occurred, the government's initial measure was implementing disinfection, hygiene guidelines, and social distancing [40]. However, the above actions are only for the initial response when there is no vaccine. Vaccination is considered the best way to fight the COVID-19 pandemic and return to normal economic and social activities [41]. Vaccination is influenced by the perceived risk of disease and social factors that make it possible to hesitate or decide to vaccinate. However, several vaccination-related incidences have increased vaccine hesitancy in many nations, most notably Vietnam, during the previous decade [12]. According to WHO, vaccine hesitancy is defined as vaccine rejection notwithstanding the availability of vaccination services; vaccine hesitancy has been documented in more than 90% of the world's countries [42]. It is a fact that vaccination is currently considered the most likely method for limiting the spread of COVID-19. Similarly, it explored how vaccination has

become a cause of fear and a target for misinformation—demonstrating how the media has played a role in perpetuating vaccination fears despite overwhelming evidence of vaccine safety and effectiveness. Individual vaccination safety opinions range from facts and theories to propaganda and misleading claims [43].

Perceived Severity of COVID-19 (PSC): Perceived severity is an individual's expectation of loss and risks, including negative uncertainties [44]. The perception of risk is the perceived risk to health in the spread of COVID-19. Psychological factors influence people's intention to vaccinate. Based on the protective motivation theory (PMT), Rogers and Maddux [45] show that the perceived risks related to ourselves (e.g., being infected with COVID-19) will lead to behaviors protection like vaccination. According to PMT theory, individuals are highly motivated to self-protection when they believe they are vulnerable to risk (high threat appraisal) and are more inclined to implement preventive measures such as vaccination (high coping appraisal). Understanding public risk perception is becoming increasingly important as the number of deaths from the disease rises worldwide [46]. The perceived influence of the disease's danger and the intensity of symptoms are crucial predictors of decisions to the vaccine. While the development of COVID-19 vaccinations has progressed internationally, some people are still reluctant to undergo COVID-19 immunization. In the current situation, vaccination against COVID-19 is the quickest way to resume their normal life. At the same time, PMT is also approached as a source of information on dealing with risks such as vaccination [47]. Individuals access information flows about COVID-19 risk countermeasures (e.g., vaccines) to be fully informed before making an intention to vaccinate.

However, due to various subjective and objective concerns, not everyone is willing to inject the COVID-19 vaccination. The most prevalent reasons were perceived dangers versus advantages, religious views, and a lack of information and understanding. The intention to vaccinate is also influenced by awareness and misinformation from a variety of sources. Vaccines, in reality, are a part of the "social world", which means that a variety of elements (previous trials—competition for health services, family history, feelings of control, etc.), chats with friends, and so on, all influence vaccinations. They hesitate to inject because they understand the danger of the SARS-CoV 2 virus that can cause many diseases to the human respiratory system and do not want to inject. After all, there may be side effects that can cause serious harm after injection danger to their lives. Thus, we hypothesized the following:

Hypothesis 1(H1). *Perceived Severity of COVID-19 (PSC) has a positive impact on an individual's Perceived COVID-19 Vaccine (PCV).*

Hypothesis 2(H2). *Perceived Severity of COVID-19 (PSC) has a positive impact on an individual's behavioral COVID-19 vaccination intention (INT).*

Hypothesis 3(H3). *Perception COVID-19 Vaccine (PCV) has a positive impact on an individual's behavioral COVID-19 vaccination intention (INT).*

Trust in government intervention strategies (TRS): The Vietnamese government had an effective anti-epidemic strategy from the onset of the COVID-19 pandemic to June 2021, when the number of infections and deaths was under control (the time of the survey and research was the period when the outbreaks in Vietnam were basically under control, however, by the end of July 2021, the situation started to get complicated in some southern provinces of Vietnam). Therefore, people have certain beliefs about the government's anti-epidemic strategy. Several studies have shown that beliefs influence intention or hesitation to vaccinate. Trust in the government or epidemic prevention policy plays a role in people's intention to vaccinate [43,48]. Trust in government policy lies in concrete actions and reliable or official information on epidemic prevention, vaccines, and vaccination processes being released quickly. During the COVID-19 pandemic, false information or fake news with the nature of conspiracy theories to confuse people often appear on social media

channels [49]. Therefore, the government's provision of accurate information will help people understand correctly the COVID-19 situation as well as the issue of vaccination. At the same time, information about the health system and complete information about vaccines will make people more confident in the health system in vaccination work. From there, they will trust the government's policy and the health system to be more ready to vaccinate. Hence, we proposed:

Hypothesis 4(H4). *Trust in government intervention strategies (TRS) has a positive impact on an individual's behavioral COVID-19 vaccination intention (INT).*

Social Media (SOM): In today's society, social media is one of the powerful communication tools available. The effects of social media use on behavioral health changes include that social media coverage of a pandemic might exaggerate public anxiety and encourage people to adopt preventative measures [50]. Previous research has demonstrated that mainstream media consumption can influence or prevent negative changes in health-related behaviors in large populations; for example, listening to the radio and reading the newspaper were associated with an increased likelihood of vaccination [51]. The infectious COVID-19 pandemic outbreaks necessitate immediate action for the government and the whole population. Mass media's abundance of information and usage in conveying the COVID-19 virus may contribute to overreaction, unjustified public panic, and an excessively gloomy perception of the existing risk. In contrast, the press and social media play an essential role in disseminating official information about the COVID-19 epidemic in Vietnam; the issue of fake news continues to be a concern. According to the Ministry of Information and Communications, the press published 560,048 news stories and articles on COVID-19 translation between 1 January and 31 May 2020.

Regarding recent police statistics, nearly 300,000 news reports were uploaded to the internet, including websites, blogs, and forums, and approximately 600,000 news stories, articles, films, and clips about the illness were shared on social media sites [52]. Additionally, social media is effective in promoting health [53]. The government has made proactive forecasts and specific plans in response to fake news, most notably during the COVID 19 outbreak. Thus, posting official and trustworthy information on government-sponsored social networking sites will build public confidence in the government's strategy. People's trust increases when the information they receive comes from government agencies or reputable medical units [48]. After selecting reliable information ends, they feel more confident in the government and the health system, and their intention to vaccinate will be increased [54]. Along with hypothesis 4, we also hypothesized the following:

Hypothesis 5(H5). *Social Media (SOM) has a significant direct effect on individual's trust in government intervention strategies (TRS).*

Hypothesis 6(H6). *Social Media (SOM) has a significant direct effect on an individual's behavioral COVID-19 vaccination intention (INT).*

Social Influence (SOI): Individuals' behaviors are often influenced by norms in the community they live [55]. A person's behavior can be affected by external factors (social, personal), which is a poor indicator of behavioral intention. The subject norm in the context of COVID-19 will focus on human behavior against the virus. The related behaviors of people around, family, friends will affect your perception as well as your behavior [56]. In the case of people around/negative social impact on the issue of vaccination (the risk encountered when vaccination happens the bad information people often encounter when consulting people around) reduce intention to vaccinate. In addition, the fact that people around have a good awareness of vaccines and are willing to vaccinate against COVID-19 makes that individual also have a higher intention to vaccinate. Finally, we hypothesized the following:

Hypothesis 7(H7). *Social Influence (SOI) has a significant direct effect on an individual's behavioral COVID-19 vaccination intention (INT).*

As a result, it is critical to research the elements that impact COVID-19 vaccination intention, particularly those socially connected with COVID-19 risk perception, vaccine perception, trust in government intervention strategies, social influence, and social media.

3. Research Methodology

3.1. Research Framework

The proposed research framework consists of 3 phases, as illustrated in Figure 1. First, the SF-AHP model is used in Phase 1 to assign fuzzy weights to criteria based on pairwise comparisons. Second, the PLS-SEM technique is used in Phase 2 to validate the hypotheses as indirect/direct effects. In Phase 3, significant PLS-SEM analysis predictions were used as input neurons for the ANN model. According to the normalized importance obtained from the multilayer perceptrons of the feed-forward-back-propagation ANN algorithm, we can find significant effects of vaccination intention and determine the accurate prediction rates.

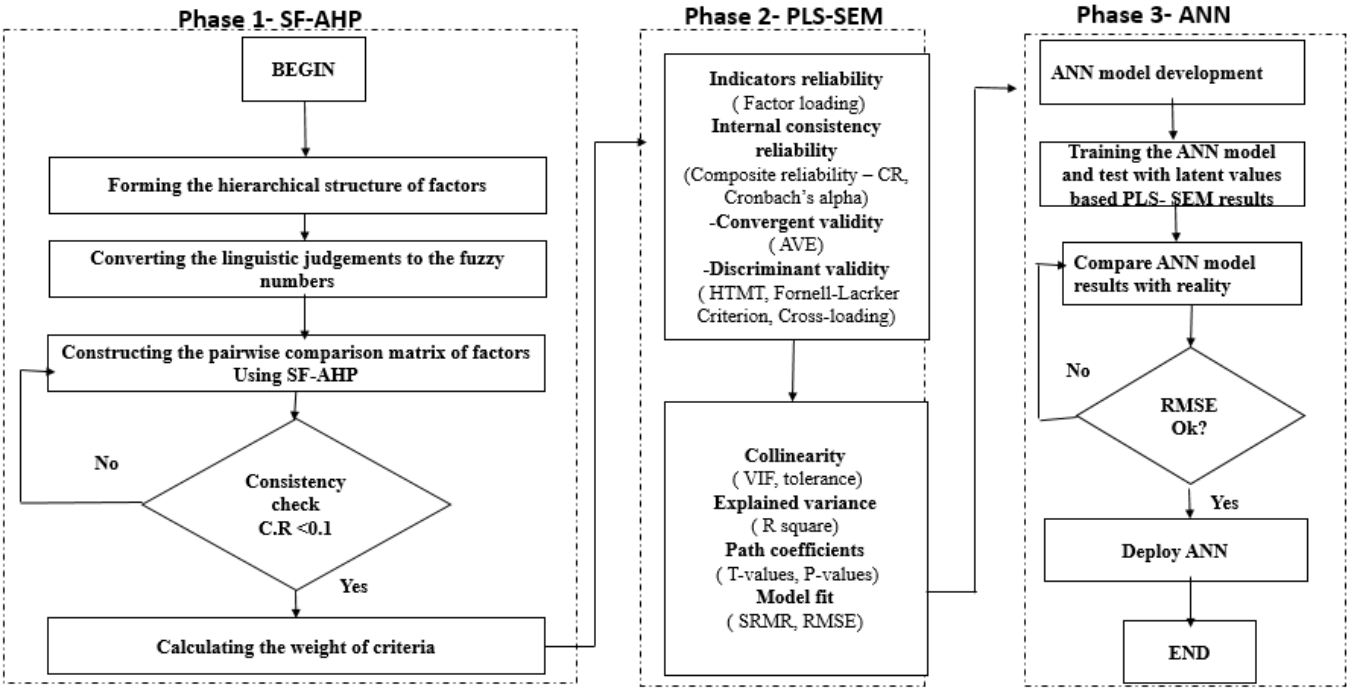


Figure 1. The research framework of SF-AHP- SEM, and ANN.

3.2. Spherical Fuzzy Analytical Hierarchy Process (SF-AHP)

Mahmood et al. [13] firstly proposed Spherical fuzzy sets (SFS) in 2018 by enlarging the 3D space of grades of satisfaction, abstinence and dissatisfaction in the interval [0, 1]. And later, Kutlu and Kahraman [16] denoted SF values with the membership, non-membership, and hesitancy degrees to present the uncertainty, as indicated in Figure 2.

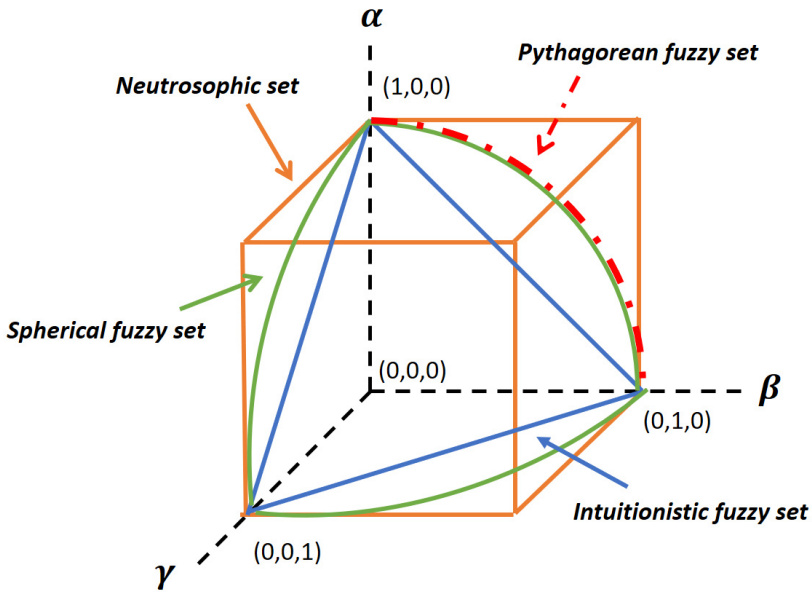


Figure 2. Geometric representations of SFS.

Definition 1. *Spherical fuzzy set* $\widetilde{F}_S$ *of the universe* X *is denoted as follows.*

$$\widetilde{F}_S = \{x, (\alpha_{\widetilde{F}_S}(x),\ \beta_{\widetilde{F}_S}(x),\ \gamma_{\widetilde{F}_S}(x)) | x \in X\} \tag{1}$$

$$\alpha_{\widetilde{F}_S}(x):\ X \to [0,1], \beta_{\widetilde{F}_S}(x): X \to [0,1], \gamma_{\widetilde{F}_S}(x): X \to [0,1] \tag{2}$$

and

$$0 \le \alpha^2_{\widetilde{F}_S}(x) + \beta^2_{\widetilde{F}_S}(x) + \gamma^2_{\widetilde{F}_S}(x) \le 1 \tag{3}$$

with $\forall x \in X$, *for each* x, $\alpha_{\widetilde{F}_S}(x)$ *for membership,* $\beta_{\widetilde{F}_S}(x)$ *for non-membership and* $\gamma_{\widetilde{F}_S}(x)$ *for hesitancy levels of* x *to* $\widetilde{F}_S$.

Definition 2. *Six basic operations of SFS are presented as follows.*

(1) Union operation

$$\begin{aligned}\widetilde{F}_S \cup \widetilde{E}_S = \{&max\{\alpha_{\widetilde{F}_S}, \alpha_{\widetilde{E}_S}\}, min\{\beta_{\widetilde{F}_S}, \beta_{\widetilde{E}_S}\}, min\{(1 \\ &- ((max\{\alpha_{\widetilde{F}_S}, \alpha_{\widetilde{E}_S}\})^2 \\ &+ (min\{\beta_{\widetilde{F}_S}, \beta_{\widetilde{E}_S}\})^2))^{0.5}, max\{\gamma_{\widetilde{F}_S}, \gamma_{\widetilde{E}_S}\}\}\}\end{aligned} \tag{4}$$

(2) Intersection operation

$$\begin{aligned}\widetilde{F}_S \cap \widetilde{E}_S = \{&min\{\alpha_{\widetilde{F}_S}, \alpha_{\widetilde{E}_S}\}, max\{\beta_{\widetilde{F}_S}, \beta_{\widetilde{E}_S}\}, max\{(1 \\ &- ((min\{\alpha_{\widetilde{F}_S}, \alpha_{\widetilde{E}_S}\})^2 \\ &+ (max\{\beta_{\widetilde{F}_S}, \beta_{\widetilde{E}_S}\})^2))^{0.5}, min\{\gamma_{\widetilde{F}_S}, \gamma_{\widetilde{E}_S}\}\}\}\end{aligned} \tag{5}$$

(3) Addition operation

$$\begin{aligned}\widetilde{F}_S \oplus \widetilde{E}_S = \{&(\alpha^2_{\widetilde{F}_S} + \alpha^2_{\widetilde{E}_S} - \alpha^2_{\widetilde{F}_S}\alpha^2_{\widetilde{E}_S})^{0.5}, \beta_{\widetilde{F}_S}\beta_{\widetilde{E}_S}, ((1-\alpha^2_{\widetilde{E}_S})\gamma^2_{\widetilde{F}_S} + (1-\alpha^2_{\widetilde{F}_S})\gamma^2_{\widetilde{E}_S} \\ &- \gamma^2_{\widetilde{F}_S}\gamma^2_{\widetilde{E}_S})^{0.5}\}\end{aligned} \tag{6}$$

(4) Multiplication operation

$$\widetilde{F}_S \otimes \widetilde{E}_S = \{\alpha^2_{\widetilde{F}_S}\alpha^2_{\widetilde{E}_S}, (\beta^2_{\widetilde{F}_S} + \beta^2_{\widetilde{E}_S} - \beta^2_{\widetilde{F}_S}\beta^2_{\widetilde{E}_S})^{0.5}, ((1-\beta^2_{\widetilde{E}_S})\gamma^2_{\widetilde{F}_S} + (1-\beta^2_{\widetilde{F}_S})\gamma^2_{\widetilde{E}_S} - \gamma^2_{\widetilde{F}_S}\gamma^2_{\widetilde{E}_S})^{0.5}\} \tag{7}$$

(5) Multiplication by a scalar; $\sigma > 0$

$$\sigma \,.\, \widetilde{F}_S = \{(1 - (1-\alpha^2_{\widetilde{F}_S})^{\sigma})^{0.5}, \beta^{\sigma}_{\widetilde{F}_S}, ((1-\alpha^2_{\widetilde{F}_S})^{\sigma} - (1-\alpha^2_{\widetilde{F}_S} - \gamma^2_{\widetilde{F}_S})^{\sigma})^{0.5}\} \tag{8}$$

(6) Power of F_S; $\sigma > 0$

$$\widetilde{F}^{\sigma}_S = \{\alpha^{\sigma}_{\widetilde{F}_S}, (1-(1-\beta^2_{\widetilde{F}_S})^{\sigma})^{0.5}, ((1-\beta^2_{\widetilde{F}_S})^{\sigma} - (1-\beta^2_{\widetilde{F}_S} - \gamma^2_{\widetilde{F}_S})^{\sigma})^{0.5}\} \tag{9}$$

Definition 3. *For these SFSs $\widetilde{F}_S = (\alpha_{\widetilde{F}_S}, \beta_{\widetilde{F}_S}, \gamma_{\widetilde{F}_S})$ and $\widetilde{E}_S = (\alpha_{\widetilde{E}_S}, \beta_{\widetilde{E}_S}, \gamma_{\widetilde{E}_S})$, the followings are valid under the condition $\sigma, \sigma_1, \sigma_2 > 0$.*

$$\widetilde{F}_S \oplus \widetilde{E}_S = \widetilde{E}_S \oplus \widetilde{F}_S \tag{10}$$

$$\widetilde{F}_S \otimes \widetilde{E}_S = \widetilde{E}_S \otimes \widetilde{F}_S \tag{11}$$

$$\sigma(\widetilde{F}_S \oplus \widetilde{E}_S) = \sigma\widetilde{F}_S \oplus \sigma\widetilde{E}_S \tag{12}$$

$$\sigma_1\widetilde{F}_S \oplus \sigma_2\widetilde{F}_S = (\sigma_1+\sigma_2)\widetilde{F}_S \tag{13}$$

$$(\widetilde{F}_S \otimes \widetilde{E}_S)^{\sigma} = \widetilde{F}^{\sigma}_S \otimes \widetilde{E}^{\sigma}_S \tag{14}$$

$$\widetilde{F}^{\sigma_1}_S \otimes \widetilde{F}^{\sigma_2}_S = \widetilde{F}^{\sigma_1+\sigma_2}_S \tag{15}$$

Definition 4. *Spherical weighted arithmetic mean (SWAM) concerning $w = (w_1, w_2, \ldots, w_n)$; $w_i \in [0, 1]$; $\sum_{i=1}^{n} w_i = 1$, SWAM is defined as follows.*

$$\begin{aligned} SWAM_w(\widetilde{F}_{S1}, \ldots, \widetilde{F}_{Sn}) &= w_1\widetilde{F}_{S1} + w_2\widetilde{F}_{S2} + \ldots + w_n\widetilde{F}_{Sn} \\ &= \left\{ \left[1 - \prod_{i=1}^{n}(1-\alpha^2_{\widetilde{F}_{Si}})^{w_i}\right]^{0.5}, \right. \\ &\left. \prod_{i=1}^{n}\beta^{w_i}_{\widetilde{F}_{Si}}, \left[\prod_{i=1}^{n}(1-\alpha^2_{\widetilde{F}_{Si}})^{w_i} - \prod_{i=1}^{n}(1-\alpha^2_{\widetilde{F}_{Si}} - \gamma^2_{\widetilde{F}_{Si}})^{w_i}\right]^{0.5} \right\} \end{aligned} \tag{16}$$

Definition 5. *Spherical weighted geometric mean (SWGM) concerning $w = (w_1, w_2, \ldots, w_n)$; $w_i \in [0, 1]$; $\sum_{i=1}^{n} w_i = 1$, SWGM is defined as follows.*

$$\begin{aligned} SWGM_w(\widetilde{F}_{S1}, \ldots, \ddot{F}_{Sn}) &= \widetilde{F}^{w_1}_{S1} + \widetilde{F}^{w_2}_{S2} + \ldots + \widetilde{F}^{w_n}_{Sn} \\ &= \prod_{i=1}^{n}\alpha^{w_i}_{\widetilde{F}_{Si}}, \left[1 - \prod_{i=1}^{n}(1-\beta^2_{\widetilde{F}_{Si}})^{w_i}\right]^{0.5}, \left[\prod_{i=1}^{n}(1-\beta^2_{\widetilde{F}_{Si}})^{w_i} \right. \\ &\left. - \prod_{i=1}^{n}(1-\beta^2_{\widetilde{F}_{Si}} - \gamma^2_{\widetilde{F}_{Si}})^{w_i}\right]^{0.5} \end{aligned} \tag{17}$$

First, the SF-AHP model [16] is applied to identify criteria weights with five steps:

Step 1: A hierarchical framework is organized with research goal in level 1 and the proposed criteria $C = \{C_1, C_2, \ldots, C_n\}$ with $n \geq 2$ in level 2.

Step 2: Pairwise comparison matrices are conducted in terms of linguistic scales (Table 1). Score indices (SI) are calculated by Equations (18) and (19):

$$SI = \sqrt{\left|100 * \left[(\alpha_{\widetilde{F}_S} - \gamma_{\widetilde{F}_S})^2 - (\beta_{\widetilde{F}_S} - \gamma_{\widetilde{F}_S})^2\right]\right|} \tag{18}$$

for AMI, VHI, HI, SMI, and EI.

$$\frac{1}{SI} = \frac{1}{\sqrt{\left|100 * \left[(\alpha_{\widetilde{F}_S} - \gamma_{\widetilde{F}_S})^2 - \left((\beta_{\widetilde{F}_S} - \gamma_{\widetilde{F}_S})^2\right]\right|}} \tag{19}$$

for EI, SLI, LI, VLI, and ALI.

Table 1. SF-AHP linguistic terms.

Scales	(α,β,γ)	Score Index (SI)
Absolutely more Importance (AMI)	(0.9, 0.1, 0.0)	9
Very High Importance (VHI)	(0.8, 0.2, 0.1)	7
High Importance (HI)	(0.7, 0.3, 0.2)	5
Slightly More Importance (SMI)	(0.6, 0.4, 0.3)	3
Equally Importance (EI)	(0.5, 0.4, 0.4)	1
Slightly Low Importance (SLI)	(0.4, 0.6, 0.3)	1/3
Low Importance (LI)	(0.3, 0.7, 0.2)	1/5
Very Low Importance (VLI)	(0.2, 0.8, 0.1)	1/7
Absolutely Low Importance (ALI)	(0.1, 0.9, 0.0)	1/9

Step 3: In pairwise comparison matrices, the consistent ratio (CR) must be less than 10% to ensure that decision-makers' judgements are adequate.

Step 4: Determine the weight of each factor/criterion using the SWAM operator using Equation (20).

$$\begin{aligned} SWAM_w\left(\widetilde{F}_{S1}, \ldots, \widetilde{F}_{Sn}\right) &= w_1\widetilde{F}_{S1} + w_2\widetilde{F}_{S2} + \ldots + w_n\widetilde{F}_{Sn} \\ &= \langle \left[1 - \prod_{i=1}^{n}(1 - \alpha_{\widetilde{F}_{Si}}^2)^{w_i}\right]^{0.5}, \\ &\prod_{i=1}^{n}\beta_{\widetilde{F}_{Si}}^{w_i}, \left[\prod_{i=1}^{n}(1 - \alpha_{\widetilde{F}_{Si}}^2)^{w_i} - \prod_{i=1}^{n}(1 - \alpha_{\widetilde{F}_{Si}}^2 - \gamma_{\widetilde{F}_{Si}}^2)^{w_i}\right]^{0.5} \rangle \end{aligned} \tag{20}$$

where $w = 1/n$.

Step 5: Crisp weights of final criteria rankings are obtained by Equation (21). Normalize the criteria weights using Equation (22) and apply the spherical fuzzy multiplication given in Equation (23).

$$S\left(\widetilde{w}_j^s\right) = \sqrt{\left|100 * \left[\left(3\alpha_{\widetilde{F}_S} - \frac{\gamma_{\widetilde{F}_S}}{2}\right)^2 - \left(\frac{\beta_{\widetilde{F}_S}}{2} - \gamma_{\widetilde{F}_S}\right)^2\right]\right|} \tag{21}$$

$$\overline{w}_j^s = \frac{S\left(\widetilde{w}_j^s\right)}{\sum_{j=1}^{n} S\left(\widetilde{w}_j^s\right)} \tag{22}$$

$$\widetilde{F}_{S_{ij}} = \overline{w}_j^s.\, \widetilde{F}_{S_i} = \langle (1 - (1 - \alpha_{\widetilde{F}_S}^2)^{w_j^{-s}})^{0.5}, \beta_{\widetilde{F}_S}^{\overline{w}_j^s}, ((1 - \alpha_{\widetilde{F}_S}^2)^{w_j^{-s}} - (1 - \alpha_{\widetilde{F}_S}^2 - \gamma_{\widetilde{F}_S}^2)^{w_j^{-s}})^{0.5} \rangle \; \forall i \tag{23}$$

3.3. PLS-SEM Approach

PLS-SEM has been extensively used to examine correlations between dependent and independent variables [22,57]. Meanwhile, PLS-SEM is also advantageous to test hypotheses [37]. Additionally, PLS-SEM is recommended for corporate information systems research analysis for various reasons, including its small sample size, lack of normality, and capacity to operate with ordinal, nominal, and interval-scaled components in the absence of distributional presumptions [58]. As a result, PLS-SEM with Smart PLS V3.3.3 and SPSS V26 software are employed in this study to investigate the constructed research hypotheses.

3.3.1. Sampling and Collecting Data

The data collecting process was conducted online through Gmail, Facebook platforms. Because this is a new study in the context of Vietnam, the questionnaire was surveyed in two phases: The first phase, the research survey on 15 experts to assess the understandable and logical level of the questionnaire. After collecting opinions, appropriate contextual adjustments were made and then conducted them in the second phase. Phase 2, the data was officially collected. The online survey was conducted over two months, from June to July 2021. The questionnaire was constructed as follows. The construct elements were quantified using 5-point Likert scales ranging from "strongly disagree" to "strongly agree".

3.3.2. Quantitative Analysis

(1) Reliability test: The reliability analysis results are shown through two indexes: Cronbach's Alpha coefficient is greater than 0.7, and Composite Reliability (CR) is greater than 0.7 [22,59]. At the same time, this study also evaluates the convergence value of the constructs through the factor loading coefficient greater than 0.5 and the Average Variance Extracted (AVE) greater than 0.5. Thus, when the constructs achieve convergence and reliability, the analytical results for the constructs by items will be reliable [22,59].

(2) Discriminant validity: In addition to assessing the confidence value and the convergence value, the analysis requires the constructs to ensure distinctiveness from each other. Two commonly used evaluation methods are: AVE's square root is greater than the corresponding correlation coefficient between the two constructs, and HTMT is less than 0.85 [22,59].

(3) Path Analysis: The analytical results of the PLS-SEM structural model were used to determine the relationship among five factors predicting behavioral intention to get vaccines against the COVID-19 pandemic [22,59].

3.4. ANN Algorithm

Numerous applications of ANN models consisting of three layers: input, hidden, and output [60–63] have been conducted in various research fields. The activation function connects each layer. The sigmoid or hyperbolic tangent function is frequently employed as an activation function in ANN. Similar to Leong et al. [62], multilayer perceptrons (MLP) were used with a "feed-forward-back-propagation" algorithm where the significant predictors from PLS-SEM path analysis are used as the input neurons.

Additionally, tenfold cross-validation is performed to determine the trained network's prediction precision, which is compatible with the suggestions made by the previous research [60–63]. Over-fitting is avoided by dividing the data into two portions, with 90% assigned to training and 10% to testing [57]. Although PLS-SEM is vigorous against non-normal distribution, it cannot capture nonlinear relationships [64]. Therefore, to keep advantages and eliminate PLS-SEM's limitations, ANN analysis is utilized in phase 3.

4. Analytical Results

4.1. A Case Study in Vietnam

A quantitative approach was used in conjunction with questionnaires to collect the necessary data for this research. An online questionnaire survey of 15 experts was used to

collect data following COVID-19. Data was gathered by referring to experienced experts in health care management and the disease control department. Three experts work for the Ministry of Health in Vietnam, five scholars work at medical universities, and the remaining group is made up of experienced doctors and nurses who serve in disease-ridden areas (Ha Noi, Ho Chi Minh, Binh Duong, Da Nang, Long An, Tien Giang). Figure 3 illustrates the conceptual framework and hypotheses for evaluating behavioral intention to get a vaccination against COVID-19 in this study.

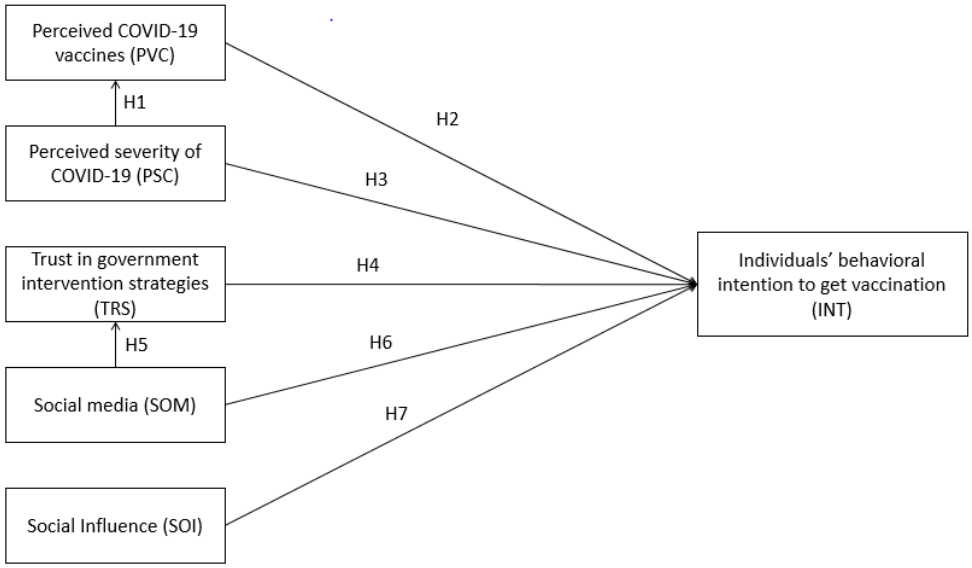


Figure 3. The conceptual framework and hypotheses.

4.2. SF-AHP Results

In Phase 1, the SF-AHP procedure presented below calculates the relative importance of factors influencing individuals' intention to receive COVID-19 vaccines by a panel of 15 decision-makers. Experts use linguistic terms to structure the consolidated pairwise comparisons of the factors (Table 1). Second, as shown in Tables 2–4, CR computations determine the pairwise comparison matrix's consistency. The CR of pairwise comparison matrices is calculated as follows:

$$\text{PCV in respect to TRS} = \frac{SI_{\text{PCV in respect to TRS}}}{SUM_{TRS}} = \frac{3.021}{5.6069} = 0.539$$

$$MEAN_{PCV} = \frac{0.481 + 0.539 + 0.463 + 0.443 + 0.431}{5} = 0.4714$$

$$WSV = \begin{bmatrix} 1.000 & 3.021 & 3.342 & 3.871 & 5.279 \\ 0.331 & 1.000 & 1.485 & 1.957 & 2.493 \\ 0.299 & 0.674 & 1.000 & 1.411 & 1.460 \\ 0.258 & 0.511 & 0.709 & 1.000 & 2.025 \\ 0.189 & 0.401 & 0.685 & 0.494 & 1.000 \end{bmatrix} \times \begin{bmatrix} 0.4714 \\ 0.1941 \\ 0.1367 \\ 0.1187 \\ 0.0791 \end{bmatrix} = \begin{bmatrix} 2.3918 \\ 0.9826 \\ 0.6915 \\ 0.5967 \\ 0.3985 \end{bmatrix}$$

$$CV = \begin{bmatrix} 2.3918 \\ 0.9826 \\ 0.6915 \\ 0.5967 \\ 0.3985 \end{bmatrix} / \begin{bmatrix} 0.4714 \\ 0.1941 \\ 0.1367 \\ 0.1187 \\ 0.0791 \end{bmatrix} = \begin{bmatrix} 5.0740 \\ 5.0610 \\ 5.0596 \\ 5.0289 \\ 5.0356 \end{bmatrix}$$

$$\lambda_{max} = \frac{5.0740 + 5.0610 + 5.0596 + 5.0289 + 5.0356}{5} = 5.0518$$

$$CI = \frac{\lambda_{max} - n}{n-1} = \frac{5.0518 - 5}{5-1} = 0.0130$$

$$CR = \frac{CI}{RI} = \frac{0.0130}{1.12} = 0.0116$$

with RI = 1.12.

Table 2. Pairwise comparison matrix.

Factors	Left Factor Is More Important					Right Factor Is More Important				Factors
	AMI	VHI	HI	SMI	EI	SLI	LI	VLI	ALI	
PCV		1	5	7	1	1				TRS
PCV	2	2	2	6	3					SOM
PCV	2	4	3	4	1	1				PSC
PCV	3	5	4	2	1					SOI
TRS			3	5	3	4				SOM
TRS		1	3	4	6	1				PSC
TRS	1	2	2	5	4	1				SOI
SOM		1	2	3	6	3				PSC
SOM		1	3	3	4	4				SOI
PSC	1	1	4	2	5	2				SOI

Table 3. Crisp matrix for Composite Reliability.

Factors	PCV	TRS	SOM	PSC	SOI
PCV	1.000	3.021	3.342	3.871	5.279
TRS	0.331	1.000	1.485	1.957	2.493
SOM	0.299	0.674	1.000	1.411	1.460
PSC	0.258	0.511	0.709	1.000	2.025
SOI	0.189	0.401	0.685	0.494	1.000
SUM	2.0780	5.6069	7.2199	8.7327	12.2566

Table 4. Normalized matrix for Composite Reliability.

Factors	PCV	TRS	SOM	PSC	SOI	MEAN	WSV	CV
PCV	0.481	0.539	0.463	0.443	0.431	0.4714	2.3918	5.0740
TRS	0.159	0.178	0.206	0.224	0.203	0.1941	0.9826	5.0610
SOM	0.144	0.120	0.139	0.162	0.119	0.1367	0.6915	5.0596
PSC	0.124	0.091	0.098	0.115	0.165	0.1187	0.5967	5.0289
SOI	0.091	0.072	0.095	0.057	0.082	0.0791	0.3985	5.0356

Since CR = 0.0116 $\leq$ 0.1, the pairwise comparison matrix does not need to be re-evaluated.

Thirdly, we incorporated a fuzzy spherical comparison matrix (Table 5) and the obtained SF-AHP weights are shown in Table 6. To demonstrate, we calculated the weight of PCV criteria in the following steps.

Table 5. Integrated spherical fuzzy comparison matrix.

Factors	PCV	TRS	SOM	PSC	SOI
PCV	(0.500, 0.400, 0.400)	(0.619, 0.381, 0.275)	(0.648, 0.341, 0.283)	(0.678, 0.335, 0.238)	(0.737, 0.270, 0.201)
TRS	(0.357, 0.642, 0.261)	(0.500, 0.400, 0.400)	(0.535, 0.454, 0.310)	(0.571, 0.393, 0.326)	(0.606, 0.377, 0.301)
SOM	(0.292, 0.704, 0.242)	(0.421, 0.567, 0.303)	(0.500, 0.400, 0.400)	(0.535, 0.434, 0.330)	(0.539, 0.446, 0.311)
PSC	(0.268, 0.735, 0.196)	(0.370, 0.601, 0.309)	(0.399, 0.572, 0.317)	(0.500, 0.400, 0.400)	(0.584, 0.395, 0.307)
SOI	(0.223, 0.778, 0.160)	(0.329, 0.661, 0.268)	(0.402, 0.583, 0.296)	(0.340, 0.645, 0.275)	(0.500, 0.400, 0.400)

Table 6. Results of SF-AHP weights.

	SF-AHP Weights (α,β,γ)	Calculations to Obtain Crisp Weights $S\left(\tilde{w}^s\right)$	Crisp Weights $\tilde{w}^s$
PCV	(0.647, 0.342, 0.280)	17.988	0.273
TRS	(0.525, 0.444, 0.326)	14.089	0.214
SOM	(0.471, 0.499, 0.327)	12.465	0.189
PSC	(0.444, 0.525, 0.320)	11.716	0.178
SOI	(0.374, 0.599, 0.300)	9.713	0.147

Spherical fuzzy weights of criteria PCV with $(\alpha,\beta,\gamma) = (0.647, 0.342, 0.280)$

$$\boldsymbol{\alpha_{PCV}} = \left[1-\prod_{i=1}^{n}\left(1-\alpha_{F_{Si}}^2\right)^{w_i}\right]^{0.5}$$

$$= \left[1-\left(1-0.5^2\right)^{\frac{1}{5}} * \left(1-0.619^2\right)^{\frac{1}{5}} * \left(1-0.648^2\right)^{\frac{1}{5}} * \left(1-0.678^2\right)^{\frac{1}{5}} * \left(1-0.737^2\right)^{\frac{1}{5}}\right]^{0.5} = 0.647$$

$$\boldsymbol{\beta_{PCV}} = \prod_{i=1}^{n}\beta_{F_{Si}}^{w_i} = 0.4^{\frac{1}{5}} * 0.381^{\frac{1}{5}} * 0.341^{\frac{1}{5}} * 0.335^{\frac{1}{5}} * 0.270^{\frac{1}{5}} = 0.342$$

$$\boldsymbol{\gamma_{PCV}} = \left[\prod_{i=1}^{n}\left(1-\alpha_{F_{Si}}^2\right)^{w_i} - \prod_{i=1}^{n}\left(1-\alpha_{F_{Si}}^2-\gamma_{F_{Si}}^2\right)^{w_i}\right]^{0.5}$$

$$= \left[\left(1-0.5^2\right)^{\frac{1}{5}} * \left(1-0.619^2\right)^{\frac{1}{5}} * \left(1-0.648^2\right)^{\frac{1}{5}} * \left(1-0.678^2\right)^{\frac{1}{5}} * \left(1-0.737^2\right)^{\frac{1}{5}} - \left(1-0.5^2-0.4^2\right)^{\frac{1}{5}} * \left(1-0.619^2-0.275^2\right)^{\frac{1}{5}} * \left(1-0.648^2-0.283^2\right)^{\frac{1}{5}} * \left(1-0.678^2-0.238^2\right)^{\frac{1}{5}} * \left(1-0.737^2-0.201^2\right)^{\frac{1}{5}}\right]^{0.5} = 0.280$$

$$\boldsymbol{S}\left(\widetilde{\boldsymbol{w}}_{\boldsymbol{PCV}}^{\boldsymbol{s}}\right) = \sqrt{\left|100 * \left[\left(3\alpha_{\overline{F}_s} - \frac{\gamma_{\overline{F}_s}}{2}\right)^2 - \left(\frac{\beta_{\overline{F}_s}}{2} - \gamma_{\overline{F}_s}\right)^2\right]\right|}$$

$$= \sqrt{\left|100 * \left[\left(3 * 0.647 - \frac{0.280}{2}\right)^2 - \left(\frac{0.342}{2} - 0.280\right)^2\right]\right|}$$

$$= 17.988$$

$$\overline{\boldsymbol{w}}_{\boldsymbol{PCV}}^{\boldsymbol{s}} = \frac{S\left(\widetilde{w}_j^s\right)}{\sum_{J=1}^{n} S\left(\widetilde{w}_j^s\right)} = \frac{10.977}{17.988+14.089+12.465+11.716+9.713} = 0.273$$

As the results of the abovementioned calculations, the crisp weights of five factors are determined. The most significantly correlated criterion to INT is PVC with 0.273, followed by TRS with 0.214. Meanwhile, SOM is ranked at the third position with 0.189, followed by PSC (0.178), and SOI is last (0.147). Based on SF-AHP results, no factors are eliminated in this study. Therefore, all five factors are considered in the second phase of the PLS-SEM approach.

4.3. PLS-SEM Results

4.3.1. Sample Characteristics

Regarding the demographics analysis from Table 7, the proportion of males is larger than that of women, with 474 online survey responses (men have 264 people, accounting for 55.6%; women are 210 people, accounting for 44.4%). The surveyed age group under 35 years old is 327 people, accounting for 68.8%, followed by the group of 35 to 45 years old (116 people, accounting for 24.6%), and finally the group from 46 to 65 years old with 31 people accounting for 6.5%. The marital status of the survey subjects is mainly unmarried (310 people, accounting for 65.3%), and the remaining 34.7% are married (164 people). In terms of income, the group between 10 VND million and 15 VND million has the highest proportion (211 individuals, 44.4%), while the group under 10 VND million has the lowest share (81 people, 17.3%). Employees at private companies were questioned the most (201 people, or 42.5%), whereas workers in industrial zones were surveyed the least (16 people, accounting for 3.4%). The primary level of education questioned is university graduation (333 individuals, or 70.1%), followed by master's degree (12.8%), doctor's degree (50 people, 10.5%), and high school and less (30 people, 6.5%). When asked about their likelihood of contracting COVID-19, participants generally assigned a risk of infection of between 20% and 40% (166 people accounting for 34.9%). Finally, this study questioned participants about their relatives who died from COVID-19; the data indicated that 380 persons (80.2%) had no relatives and 94 people with relatives died due to COVID-19 (19.8%).

Table 7. Results of descriptive analysis.

	n	%		*n*	%
Gender			**Status**		
Female	210	44.4	Other	310	65.3
Male	264	55.6	Married	164	34.7
Age			**Income**		
Under 35	327	68.8	<10 mil	81	17.3
35 to 45	116	24.6	From 10 mil to 15	211	44.4
46 to 65	31	6.5	From 15 mil to 20 mil	69	14.5
			>20 mil	113	23.8
Job					
Private office staff	201	42.5	**Possibility of infection**		
Public Officials	48	10.1	0–20%	152	32.2
Self-employed	94	19.8	20–40%	166	34.9
Industrial workers	16	3.4	40–60%	94	19.8
Other	115	24.2	60–100%	62	13.1
Education			**Whose relatives die**		
High school and below	30	6.5	No	380	80.2
University graduate	333	70.1	Yes	94	19.8
Master	61	12.8			
Doctor	50	10.5			

4.3.2. Assessment of the Measurement Model

PLS-SEM bootstrapping with 10,000 samples was used to determine the model's statistical significance. Table 8 shows the results of the PLS-SEM analysis. Their reliability and validity were assessed, as well as the degree of consistency of their scores. The analytical results indicate that all factors satisfy the reliability when measuring the observed variables (Cronbach's Alpha coefficient is greater than 0.7 and CR is greater than 0.7). Additionally, the factor loading coefficients of all items between 0.697 and 0.936 are larger than 0.5, and the factor AVE is greater than 0.5, suggesting that all factors fulfill the convergence value. Additionally, no components are deleted from their original state.

Table 8. Results of PLS-SEM analysis.

Scales' Items/Sources	Loading	Cronbach's Alpha
Perceived Severity of COVID-19 (PSC) adapted from [37,41,47,65];	**CR = 0.890, AVE = 0.599**	
PSC 1_ The COVID-19 pandemic has a high mortality rate.	0.801	
PSC 2_ Worrying about yourself, relatives, and colleagues who may be infected with COVID-19.	0.824	
PSC 3_ Recognizing the possibility of a COVID-19 pandemic breaking out in the area where you live and work.	0.747	0.867
PSC 4_ Risk Perception of infection during concentrated isolation.	0.775	
PSC 5_ Risk Perception of infection during self-isolation	0.728	
PSC 6_ Risk perception of distance guidance during self-isolation.	0.766	
Perceived COVID-19 Vaccines (PVC) adapted from [37,65,66];	**CR = 0.952, AVE = 0.772**	
PVC 1_ Perceive that getting vaccinated against COVID-19 reduces the risk of the disease.	0.849	
PVC2_ Perceive that getting vaccinated against COVID-19 reduces the severity of the disease.	0.831	
PVC 3_ Perceive that vaccination against COVID-19 is required to prevent disease outbreaks.	0.884	0.941
PVC 4_ Perceive that vaccination against COVID-19 is good for the community.	0.913	
PVC5_ Perceive that vaccination against COVID-19 helps economic and social activities return to normal soon.	0.929	
PVC6_ Research on a COVID-19 vaccine is needed in the context of many new variants.	0.862	
Social Influence (SOI) adapted from [56,67,68];	**CR = 0.922, AVE = 0.799**	
SOI1_ impact of family members on your decision to get the COVID-19 vaccine.	0.936	
SOI2_ Impact of friends and colleagues on your decision to get the COVID-19 vaccine.	0.928	0.876
SOI3_ In general, you are easily influenced by people around you about getting the COVID-19 vaccine.	0.811	
Social Media (SOM) adapted from [69–71];	**CR = 0.903, AVE = 0.756**	
SOM1_ Regularly find out information about the COVID-19 vaccine on social networks.	0.867	
SOM2_ Refer to the information shared from people who have received the COVID-19 vaccine on social networks.	0.867	0.840
SOM3_ Social networks bring much helpful information to you about the COVID-19 vaccine.	0.875	
Trust in government intervention strategies (TRS) adapted from [65,72–74];	**CR = 0.926, AVE = 0.676**	
TRS1_ Trust in the government's ability to prevent COVID-19.	0.820	
TRS2_ Trust the vaccine being used by the Vietnamese government.	0.877	
TRS3_ Trust in the COVID-19 vaccine storage procedures.	0.846	0.903
TRS4_ Trust in the medical team during the COVID-19 vaccination process.	0.823	
TRS5_ Trust in the ability to manage side effects after a COVID-19 vaccine.	0.808	
TRS6_ Trust that vaccines are the most effective method of disease prevention and control COVID-19.	0.753	
Behavioral intention to get vaccination (INT) adapted from [31,71,72];	**CR = 0.890, AVE = 0.733**	
INT1_ Registered for the COVID-19 vaccine.	0.697	
INT2_ Expect to get a COVID-19 vaccine at any time.	0.936	0.817
INT3_ Ready to encourage loved ones to get vaccinated against COVID-19.	0.915	

This study employed Fornell and Larcker's method [75] to determine discriminant validity. When the square root of AVE is greater than the associated correlation coefficient, the variables are discriminating. Additionally, this study estimates the Heterotrait-Montrait (HTMT) values proposed by Henseler et al. [76] to ensure the discriminant is accurate. The results from Table 9 show a clear distinction when the HTMT is ranged from 0.431 to 0.802 lower than 0.85.

Table 9. Results of discriminant validity analysis.

	INT	PSC	PCV	SOI	SOM	TRS
INT	**0.856**					
PSC	0.539	**0.774**				
	(0.612)					
PCV	0.723	0.688	**0.879**			
	(0.802)	*(0.750)*				
SOI	0.423	0.501	0.469	**0.894**		
	(0.480)	*(0.579)*	*(0.503)*			

Table 9. *Cont.*

	INT	PSC	PCV	SOI	SOM	TRS
SOM	0.533	0.637	0.650	0.594	**0.870**	
	(0.615)	*(0.752)*	*(0.719)*	*(0.681)*		
TRS	0.621	0.598	0.658	0.396	0.527	**0.822**
	(0.689)	*(0.659)*	*(0.709)*	*(0.431)*	*(0.590)*	

Notes: 1st value = Correlation between variables; 2nd value (*italic*) = HTMT ratio; Square root of AVE (bold diagonal).

4.3.3. Multicollinearity

In addition, this study evaluates the independence of the variables through the VIF coefficient of O'Brien [77]. Table 10 shows that the model has no serious multicollinearity problem when the VIF coefficients (ranged from 1 to 2.575) are all less than 10. Therefore, the inclusion of variables in the analysis in the same model does not affect the analytical results.

Table 10. Results of PLS-SEM analysis.

		PVC	TRS	INT	VIF
H1, H2	PSC	0.688 [a]		−0.030	1; 2.316
		(0.000)		(0.552)	
H3	PVC			0.523 [a]	2.575
				(0.000)	
H4	TRS			0.244 [a]	1.915
				(0.000)	
H5, H6	SOM		0.527 [a]	0.042	1; 2.288
			(0.000)	(0.467)	
H7	SOI			0.072	1.613
				(0.173)	
	R Square	**0.474**	**0.278**	**0.566**	

Notes: PRC: Perceived Severity of COVID-19; PVC: COVID-19 vaccine perception; SOI: Social influence; SOM: Social media; TRS: Trust in government intervention strategies; numbers in brackets: standard error; [a]: significance at 1% respectively (two-tailed *t*-test).

4.3.4. Hypothesis Testing Results

PLS-SEM analysis are deployed to test the proposed hypotheses in this study (Table 10). PSC has a positive effect on PVC ($\beta = 0.688$, p-value < 1%). So Hypothesis (H1) is accepted. Hypothesis (H2) is rejected (p-value > 10%). Hypothesis (H3) is accepted with the coefficient $\beta = 0.523$ and has a statistical significance of 1%. Regarding Hypothesis (H4), TRS significantly affected INT ($\beta = 0.244$, p-value < 1%). Hypothesis (H4) is accepted. Hypothesis (H5) suggests a positive effect of SOM on TRS. Hypothesis (H5) is accepted ($\beta = 0.527$, p-value < 1%). Finally, Hypotheses (H6) and (H7) state the positive impact of SOM and SOI on INT. However, these two hypotheses were rejected with p-values both greater than 0.1. Thus, our analysis concludes that only four path coefficients were significant and relevant, as illustrated in Figure 4.

4.4. Results of ANN

This study used a feed-forward backpropagation multilayer training approach with a sigmoid activation function to train the ANN model. As a result, to validate the findings of ANN analysis, this work used the commonly used accuracy measure of Root Mean Square Error (RMSE) [78]. This study used 90% of the data points for training and 10% for testing [79].

In the ANN model, PVC, PSC, TRS, SOM, and SOI were part of the input layer (neurons), and INT was part of the output layer, as depicted in Figure 5. The model's accuracy was determined using the values of the ten networks' root mean square error (RMSE). According to Table 11, the mean RMSE for training is 0.089 to 0.106 and for testing is 0.077 to 0.112. As a result, the models are highly reliable in capturing the relationships

between predictors, and the ANN model fit is excellent [80]. Finally, we calculated the R^2, indicating that the ANN model can predict with 90% accuracy.

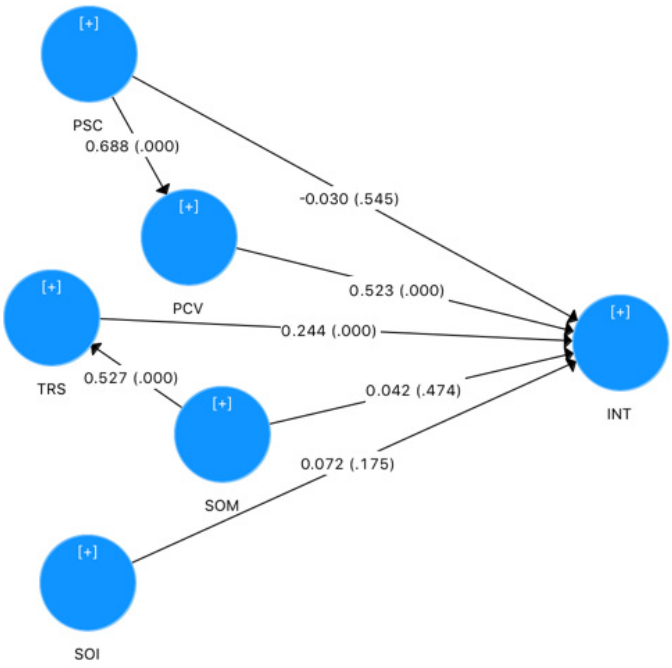


Figure 4. Structural (inner) model.

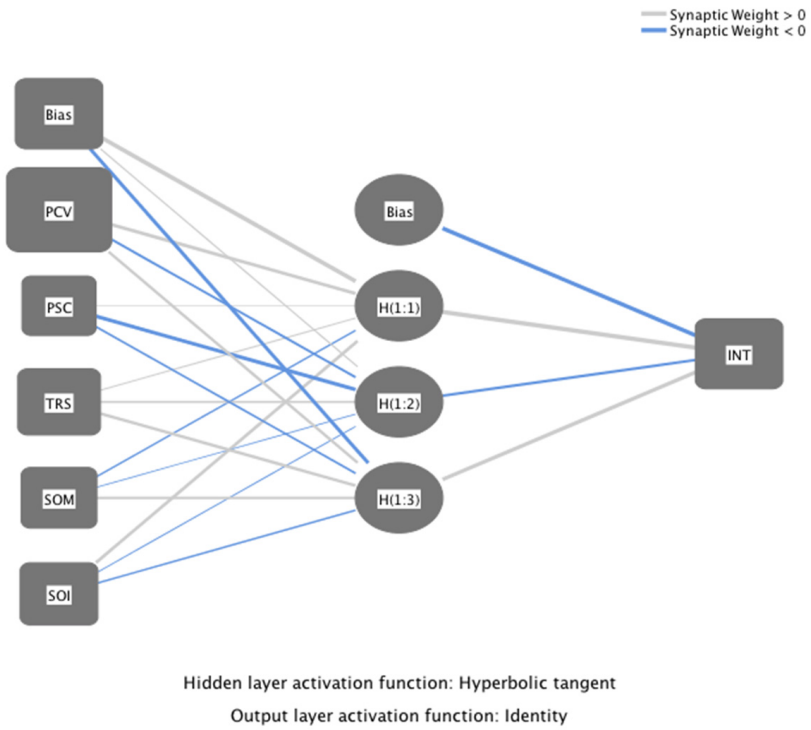


Figure 5. Nonlinear ANN model.

Table 11. Results of neural network validation.

Training			Testing		
N	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**
437	4.946	0.106	37	0.302	0.090
431	4.273	0.100	43	0.296	0.083
417	3.272	0.089	57	0.473	0.091
436	4.661	0.103	38	0.474	0.112
427	3.592	0.092	47	0.357	0.087
437	4.467	0.101	37	0.300	0.090
432	5.020	0.108	42	0.348	0.091
425	3.722	0.094	49	0.352	0.085
431	3.800	0.094	43	0.299	0.083
417	3.927	0.097	57	0.338	0.077
Mean	4.168	0.098	Mean	0.354	0.089
S.D	0.596	0.006	S.D	0.067	0.009

Note: SSE = Sum square errors, RMSE = Root mean square errors, N = sample size, S.D = Standard Deviation.

4.5. Sensitivity Analysis

In this study, sensitivity analysis evaluates the differences in the dependent variable caused by changes in the associated independent variables. It was calculated in the current study by averaging the perceived importance of PVC, PSC, TRS, and SOM as well as SOI (as independent variables) predicting INT (as dependent variable) [62,81].

Table 12 shows the sensitivity analysis results for measuring the advantages of predictors of each input neuron. The PVC is the most influential independent variable in the ANN model, with a normalized important ratio of 43.74%, for predicting intention to get the vaccination. This is followed by TRS, with an important normalized ratio of 27.16%, PSC (13.10%), SOI (10.24%), and SOM (5.76%). With the help of ANN analysis, we can conclude that the PVC is the most influential variable to predict individuals' behavioral intention to get the vaccination as it has the highest normalized importance ratio compared to the remaining factors.

Table 12. Results of sensitivity analysis for the advantages of predictors of each input neuron.

ANN	PVC	PSC	SOI	SOM	TRS
ANN (1)	0.048	0.059	0.064	0.141	0.328
ANN (2)	0.559	0.072	0.108	0.023	0.238
ANN (3)	0.560	0.044	0.136	0.065	0.194
ANN (4)	0.424	0.058	0.032	0.054	0.433
ANN (5)	0.534	0.060	0.127	0.024	0.256
ANN (6)	0.500	0.080	0.034	0.027	0.359
ANN (7)	0.218	0.218	0.217	0.164	0.256
ANN (8)	0.562	0.040	0.115	0.019	0.264
ANN (9)	0.565	0.600	0.100	0.041	0.234
ANN (10)	0.516	0.112	0.117	0.033	0.223
Average Importance	0.449	0.134	0.105	0.059	0.279
Normalized Importance (%)	43.74	13.10	10.24	5.76	27.16

Note: Dependent variable = Individuals' behavioral intention to get Vaccination (INT).

5. Discussions

Regarding PLS-SEM results, the Perceived severity of COVID-19 did not directly affect vaccination intention but only has an indirect positive effect through vaccine perception. This result was in line with the previous studies [37,82]. While individuals are aware of the risk of infection with COVID-19, they are not prepared to vaccinate because they lack sufficient knowledge about the vaccination. Also, COVID-19 is a novel virus strain that emerged between the end of 2019 and the beginning of 2020. Hence, the new vaccination

was launched in Vietnam in May 2020. As a result, people lack appropriate vaccines, prompting them to seek out information about vaccines to determine whether they are rational, safe, or effective before injecting [34].

Our findings also aligned with the study of [83]. The perceived severity of COVID-19 has a positive effect on vaccine perception. Before intending to vaccinate, people find out information about vaccines' origin, which vaccines are suitable and safe on the internet and other media. During the research process, most respondents chose good vaccination instead of immediate vaccination when given a choice. In some cases, citizens are registered by the company to vaccinate, so employees do not choose vaccines for themselves. Nevertheless, they still tend to put off waiting for the vaccination with the vaccine they prefer.

Their trust favorably influences people's desire to vaccinate in the government and the healthcare system [48]. It can be shown that extreme measures taken to manage the COVID-19 outbreak in Vietnam effectively have increased people's faith in the government. At the same time, people are given timely and accurate information about the epidemic situation to successfully respond to the government's epidemic prevention strategy. As a result, people have some misconceptions regarding Vietnam's immunization effort. People have a better mindset when the government teaches people about vaccination, and their intention to vaccinate is more significant when they trust the government's vaccination program. Our citizen interviews showed appreciation for the government's anti-epidemic efforts and trust in the public immunization plan.

Furthermore, they plan to vaccinate after the state has built trust in epidemic prevention [48]. At the same time, confidence difficulties in the health system during vaccination and epidemic prevention encourage individuals to vaccinate. The medical system assures processes such as vaccine storage, vaccination, and post-vaccination to enable patients to gradually feel more comfortable while going to medical facilities for vaccination.

Social media factors do not directly affect the intention of vaccinating, but it shows a positive effect through trust in the public immunization plan. It seems that citizens receive vaccine-related information on social media, but they may not know about being vaccinated immediately. It may be due to the different sources of social networks, such as information sources or fake news, that affect their intention of vaccinating [84,85]. Nevertheless, with the selected information from official sites or announcements issued by state agencies, people's trust in vaccinating will increase positively. People's trust rises when the information they receive comes from government agencies or reputable medical units [86]. After the screening of trusted information ends, their trust in the government will be improved, and the sense of vaccination is also more robust. Therefore, the relationship between social media, trust in government intervention strategies, and individuals' behavioral intention to get vaccination is proven through signal theories.

The other factor also belongs to the impact of society on each people themselves, social influences appear not to affect the intention of vaccinating as it can be seen that the influence from other people has no meaning on the intention of vaccinating. The unpopular information about vaccines and the number of vaccinated people up to July 2021 is not huge enough to become the effect from around people can increase or decrease the intention of vaccinating. Therefore, in this stage, the primary information comes from self-study and leads to people's intention to vaccinate or not.

6. Conclusions, Limitations and Future Works

6.1. Conclusions

This study has successfully verified social factors related to individuals' vaccination intentions in Vietnam using the novel three-staged approach combining SF-AHP, PLS-SEM, and ANN framework. Five proposed factors associated with individuals' behavioral vaccination intention based on 15 experts' opinions are considered in SF-AHP analysis, including Perceived Severity of COVID-19 (PSC), Perceived COVID-19 vaccines (PVC), Trust in government intervention strategies (TRS), Social Influence (SOI), and Social media (SOM). First, the results of SF-AHP indicated that all proposed factors correlate with INT.

Second, the data of 474 valid respondents were collected and analyzed using PLS-SEM. The PLS-SEM results reported that INT was directly influenced by PVC, TRS. In contrast, SOI had no direct effect on INT. Further, PSC and SOM moderated the relationship between PVC, TRS and INT, respectively.

To answer the research questions, the ANN was deployed to validate the previous stages and found that the best predictors of COVID-19 vaccination intention were PVC, TRS, and SOM. These results were consistent with the SF-AHP and PLS-SEM models. From the theoretical basis to the results, the research has contributed both theoretically and practically. The research results will help researchers and government agencies have appropriate policies to achieve the most effective vaccination strategy.

6.2. Theoretical Implications

First, integrating social elements with PMT in our research model has added a new theoretical dimension to individuals' behavioral desire to receive COVID-19 immunization. By including these variables, researchers will better grasp PVC, TRS, and SOM's implications on individuals' vaccination intention. This theoretical discovery may serve as the foundation for following study on the behavioral intention to immunization.

Second, by including the role of SOM as an additional variable, new theoretical contributions have been made, as there was previously little research examining its effect on vaccination intention during the COVID-19 outbreak.

Finally, the integrated ANN technique can predict factors of vaccination intention with a forecast accuracy of 90%, compared to the Spherical fuzzy MCDM model of AHP.

6.3. Practical Implications

This study has an essential contribution to the government, health facilities, and relevant agencies in preventing COVID-19 in Vietnam. In the context of the worldwide outbreak of the COVID-19 pandemic, vaccination is considered necessary to advance herd immunity and help people's lives return to normal. The faster and more vaccinations are given, the better for the host and the country. However, people are still hesitant to vaccinate because there is not enough information about the vaccine. Therefore, the government needs to have official and scientific channels of information sent to the people promptly. Information on vaccinations, efficacy, safety, or the trade-off between the danger of infection versus the risk of injury from active vaccination. Giving accurate information to the people will help them realize the critical role of vaccines and realize that vaccination is necessary even though there may still be risks after vaccination.

In addition, the information related to the capacity of the health system to serve also plays an essential role in the intention to vaccinate. Therefore, the government needs to invest in improving the service capacity of the health system throughout the process from vaccine purchase, storage, injection and post-vaccination. When people realize that the health system can ensure the necessary conditions for vaccination, they will be motivated to vaccinate. Trust is in providing vaccinations and the communication factor (Social media positively affects trust). With the positive impact of social media on people's trust, government agencies need to have accurate and transparent information channels about the health system from facilities and activities serving vaccination to create a trust for the people. As the media channels providing information related to injection activities are being widely deployed, this will increase people's trust in the government as well as the health system before making the intention to inject vaccines.

6.4. Limitations and Future Research

To begin, this research is limited in scope because it was conducted in Vietnam, and thus the findings cannot be generalized and applied to other nations. Thus, future research may incorporate a cross-national or cross-cultural perspective to broaden the scope of the current study.

Second, because the ANN model predicts with 90% accuracy, future studies may incorporate additional predictors from other theories, such as combining PMT and TPB, to increase its predictive power further.

Thirdly, this study employed a cross-sectional design, which collected respondents' responses at a single point in time. As a result, future studies may consider employing a longitudinal approach to examine temporal effects. Further, this study did not attempt to account for the moderating effects of demographic variables.

Finally, because this study focused exclusively on Vietnam's emerging economy, the conclusions cannot be generalized to other economies. As such, we propose that a future comparative study of individuals' behavioral intention to obtain vaccination in developed and developing economies be done to understand better the effect of nation development level on vaccination intention.

For another future research suggestion, we also propose the spherical fuzzy extension of entropy weighting method [87] to identify the objective weights compared with the subjective weights of SF-AHP. Furthermore, the emerging fuzzy extensions such as the T-spherical fuzzy set [88] can also be combined with other MCDM models to be applied in real-world problems.

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