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Predicting Factors Affecting the Intention to Prepare for Mitigation of Man-Made Fire Disasters in Chonburi Province, Thailand: An Integration of Structural Equation Modeling and Artificial Neural Network Hybrid Approach

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Abstract: News regarding different man-made fire disasters has been increasing for the past few years, especially in Thailand. Despite the prominent fire in Chonburi Province, Thailand, the intention to prepare has been widely underexplored. This study aimed to predict factors affecting the intention to prepare for the mitigation of man-made fire disasters in Chonburi Province, Thailand. A total of 366 valid responses through convenience sampling were utilized in this study that produced 20,496 datasets. With the 20,496 datasets, structural equation modeling and artificial neural network hybrid were utilized to analyze several factors under the extended and integrated protection motivation theory and the theory of planned behavior. Factors such as geographic perspective, fire perspective, government response, perceived severity, response cost, perceived vulnerability, perceived behavioral control, subjective norm, and attitude were evaluated simultaneously to measure the intention to prepare for a fire disaster. The results showed that geographic perspective, subjective norm, and fire experience were the most important factors affecting the intention to prepare. Other factors were significant with perceived behavioral control as the least important. In addition, the results showed how the region is prone to man-made fire disasters and that the government should consider mitigation plans to highlight the safety of the people in Chonburi Province, Thailand. This study is considered the first complete study that analyzed behavioral intention to prepare for the mitigation of man-made fire disasters in the Chonburi Province region of Thailand. The results of this study could be utilized by the government as a foundation to create mitigation plans for the citizens of Thailand. Finally, the findings of this study may be applied and extended to measure the intention to prepare for other man-made fire disasters worldwide.

Keywords: artificial neural network; Chonburi province; fire disaster; protection motivation theory; structural equation modeling

1. Introduction

Fire as one of the most prominent avoidable disasters has been evident in different regions worldwide [1,2]. It could be seen that since the 1900s, fire-related disasters have dominantly affected the increase in death [3]. Thus, it is evident that fire-related disaster is prominent worldwide and mitigation and preparation should be taken into consideration [4–9], including the man-made fire disaster. One of the countries that frequently experience man-made fire disasters is Thailand. With Thailand receiving 20 million foreign tourists since 2003, the development of the country has been crucial in all regions and provinces to engage economic development through tourism [10]. To which, Chonburi has been expanding and developing to attain greater economic development but has poor management [10]. With the continuous disaster brought about by fire breakouts, the challenge of strategic development, restoration, and safety have become a wide issue in Chonburi Province.

In Thailand, evident fire breakouts have been seen in Chonburi Province, however, this has been underexplored. In March 2017, an industrial estate in Chonburi Province caught fire and the plastic industry made it difficult to mitigate and stop the fire spread [11]. This was due to the mismanagement of chemicals in the factory, creating the man-made fire. In 2020, a large fire in the district of Chonburi Province occurred and it took 10 fire trucks two hours to mitigate the fire spread [12]. The reason for this was due to the mishandling and mismanagement of electric circuits. During April and May, two different vehicles just caught fire [13]. Moreover, on October 2021, houses in Chonburi Province caught fire in the early morning. The same incident happened a week prior [14]. In September 2021, a fire broke out in a famous nightclub in the same district of Chonburi Province which again took 10 fire trucks around three hours to mitigate the fire spread [15]. The incident indicated that a lack of breaches in the club caused the man-made fire. It is evident that the area of Chonburi Province is highly likely to suffer from fire disasters, both man-made and natural fires, yet has not been explored regarding the citizen's mitigation and intention to prepare.

Several studies from different countries have focused on the effects and behavioral aspects of dealing with natural disasters [4]. Studies from countries such as China considered coping with fire-prone locations [5]. Du et al. [5] explored disaster preparedness, disaster coping ability, and risk awareness for safety measures in China. Their study showed how the lack of fire risk reduction planning and measures was evidently not considered by the village, leading to an increase in ill events. In Russia, Porfiriev [6] showed how methodologies to mitigate natural disasters such as fires and heatwaves in Moscow were not effective against the constant trend in deaths. Moreover, dos Santos [7] considered the government and public engagement after the fires in Brazil. Their study revealed that the effect of fire hazards would lead to engagement and environmental government action. People's coordination and collaboration would lead to effective management in risk reduction [7]. The different studies have highlighted how proper government management to reduce the risk of fires should be highly considered worldwide to mitigate the aftermath.

In addition, Ong et al. [4] from the Philippines considered mitigation to prepare for "The Big One" earthquake. Their study presented how an understanding of the natural disaster leads to an increase in perceived severity and perceived vulnerability, which would lead to an indirect effect on the intention to prepare. Kurata et al. [8] determined that geographical perspective and experience would lead to an indirect significant effect on the perceived effectiveness and intention of people to flood disaster response action. Moreover, Gumasing et al. [9] presented how understanding, perceived severity, and self-efficacy led to the indirect effect on the efficacy of responses to typhoons. These different studies have utilized structural equation modeling (SEM) to highlight the causal relationship of factors affecting the behavior in regard to preparation and mitigation. It was evident from the studies how the effects of knowledge and experience would lead to people's intentions. The key highlight would be the consideration of the integration and extension of the protection motivation theory (PMT) and theory of planned behavior (TPB) to holistically measure people's intentions and response when it comes to natural disasters.

Other studies of natural disasters in Thailand have been considered. Tanwattana [16] systematized community-based disaster management in the upstream area of Thailand. However, their study focused on urban floods and only those in prone communities. Pathnak and Ahmad [17] considered recovery capacity in Thailand. Although significant findings such as coping mechanisms and the impact of flood disasters were evident, their study only focused on flood-related disasters. In addition, Okazumi and Nakasu [18] considered actual situations but focused on earthquakes and tsunamis that happened in 2011. Lastly, Fakhruddin and Chivakidakarn [19] considered early warning and disaster management for socio-economic change on influence towards disaster risk management. They highlighted how the government's different actions and plans would be one of the best solutions to mitigate natural disasters happening in the country. Despite several studies being available, no studies regarding man-made fire disasters focusing on Chonburi Province were found. In addition, the need to explore the intention to prepare for fire hazards and disasters is evidently needed.

Measuring the intention of people towards disasters such as man-made fire disasters could be done by utilizing and extending the PMT and TPB model [4,8,9]. PMT is a framework used to measure coping and threat appraisal, preceded by perception, knowledge, or understanding of a certain natural disaster. McCaughey et al. [20] presented how the intention to perform an act in relation to health-related behavior could be measured with PMT. Several factors may be considered which represent threats and coping appraisals such as perceived vulnerability, perceived severity, and response cost [21]. Covey et al. [22] discussed how individual differences should be considered upon investigating protective measures and individual harm. This indicates that PMT alone cannot holistically measure both personal behavior and health-related behaviors. Justifiably, Ong et al. [4] explored the integrated PMT and TPB and indicated how it can measure the actions and the intention of an individual to mitigate natural disasters.

TPB considers main variables such as subjective norm, perceived behavioral control, and attitude towards the behavior that affects an individual's intention [8]. Kurata et al. [8] highlighted how PMT alone has been widely considered in disaster-related studies but commonly has several limitations with regard to measurements. Gumasing et al. [9] suggested extending several factors for PMT such as behavioral variables to measure the response of individuals toward natural disasters. In this study, adapted and extended integration of PMT and TPB was utilized to measure the intention to prepare for the mitigation of fire in Chonburi Province, Thailand.

The current research utilized structural equation modeling (SEM) for the measurement of the causal relationship for intention to prepare for mitigation of disasters [23]. Gumasing et al. [9] utilized SEM to measure response to a typhoon natural disaster, similar to Kurata et al. [8]. Ong et al. [4] measured the intention to prepare for the mitigation of the "Big One" earthquake in the Philippines. Their study showed how SEM is a reliable multivariate tool to determine significant latent variables to measure people's behavior and intention. However, several limitations were noted. Following the findings by Woody [23], he indicated how mediating effects of latent variables in a framework may lead to low or insignificant relationships from the present causal relationship. Fan et al. [24] explored the structure of SEM and indicated how indirect effects far from the dependent variable would cause a low to no significant relationship. Thus, to resolve the limitation present in SEM, Duarte and Pinho [25] suggested combining SEM with another tool to help resolve the disadvantages. This study, therefore, considered an artificial neural network (ANN) to help determine key constructs that affect the intention to prepare for mitigation of fire disasters.

ANN is a machine-learning algorithm that adopted the response the human body makes through the transfer of signals from neurons to the brain [26]. Beran and Violato [27] explained how an ANN was utilized to determine the health-related behaviors of different individuals. To which, this study optimized the parameters set for running the ANN model. The different activation function of the hidden and output layer was considered, as well as the optimizer and the number of nodes present.

The aim of this study was to assess and predict factors affecting the intention to prepare for the mitigation of man-made fire disasters. With the evident fire-related disasters in the Chonburi Province region in Thailand, several factors such as geographic perspective, fire perspective, government response, perceived severity, response cost, perceived vulnerability, perceived behavioral control, subjective norm, and attitude were evaluated simultaneously to measure the intention to prepare. Through the integration of PMT and TPB, a hybrid of structural equation modeling (SEM) and artificial neural network (ANN) was utilized due to the limitation of SEM solely [26]. Thus, the results of this study could be applied and extended to other disaster-related studies to measure the intention to prepare for mitigation.

This study is considered the first complete study that analyzed behavioral intention to prepare for mitigation of fire disaster in the Chonburi Province region in Thailand. In addition, the findings may be utilized by the government to create mitigation plans applicable in Thailand, and even across different countries. Lastly, the theoretical framework and methodology applied may be considered to evaluate the behavior related to man-made fire disasters worldwide.

2. Conceptual Framework

The conceptual framework utilized in this study is presented in Figure 1. Under PMT, variables such as fire perspective (FE), perceived severity (PS), response cost (RC), and perceived vulnerability (PV) were considered. Under TPB, perceived behavioral control (PB), social norm (SN), and attitude towards behavior (AT) were considered. In addition, an extension adopted from Kurata et al. [8] was considered with variables such as geographic perspective (GP) and government response (GR) to measure intention to prepare (IP). To which, 17 hypotheses were created and tested with SEM and ANN for the distinction of significant factors affecting the intention to prepare for the mitigation of man-made fire disasters.

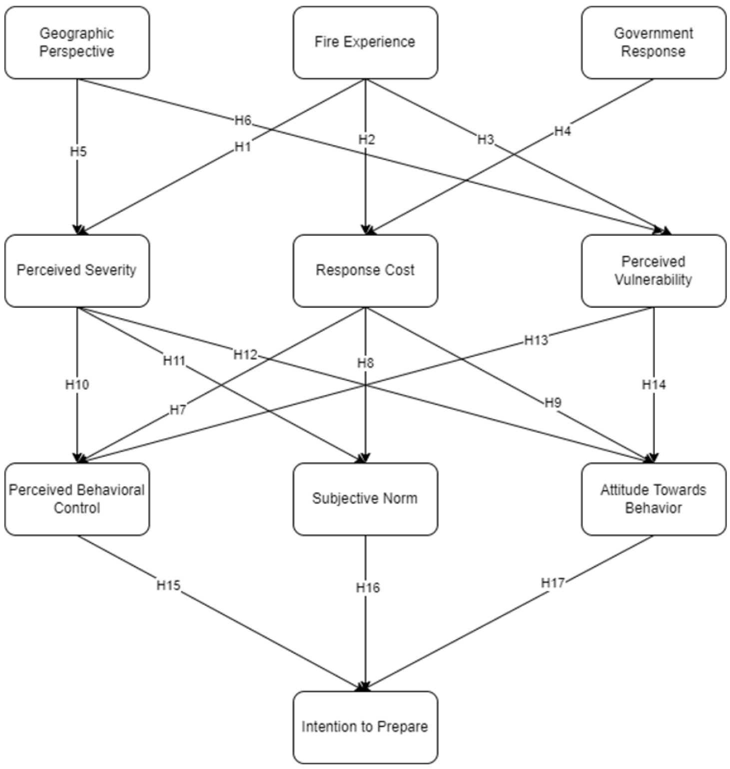

Figure 1. The conceptual research framework.

Experience from prior disasters indicates historical events that an individual was in contact with. The study by McCaughey et al. [20] presented how knowledge regarding a disaster event would lead to a significant factor affecting people's intention to evacuate an area. In addition, Ong et al. [28] presented how the individual understanding of risk would be a key factor affecting people's behavior. Their study showed how the benefits of health-related activities would drive people toward acceptance. The different studies have presented how the perception of people towards a disaster would greatly affect their perception of vulnerability, severity, and even response cost. The experience of being greatly affected by a disaster would lead to heightened PS, PV, and RC [8]. This is supported by the study by Gumasing et al. [9], wherein response efficacy is preceded by people's perception of a disaster, leading to perceived risk (associated with PV) and susceptibility (associated with PS). This would advance the individual's self-efficacy and also affect RC. Thus, the following were hypothesized:

H1: *FE has a significant direct effect on PS.*

H2: *FE has a significant direct effect on RC.*

H3: *FE has a significant direct effect on PV.*

The GR towards the present disaster affects how people would be led to act. If the government was able to present valuable information and knowledge towards a response during a calamity, individuals would have lower costs in the aftermath of the disaster [8]. To which, the experience people have with the mitigation plans would help develop instincts to build on regarding preparation for mitigation [28,29]. However, this study considered GR as a latent variable that does not directly affect PS and PV. This is because individual perceptions are being measured instead of a relative outside influence (i.e., the government). Thus, to reduce the bias of significant effect, only those that have individual perception and motives (e.g., GP and FE) were considered to directly affect PS and PV. On another note, resilience among individuals increases when a disaster would negate the tangible presence in a household [30,31]. This also relates to people's geographic location. GP affects individuals' PV and PS [8]. Mashi et al. [32] indicated how the perception of severity and vulnerability would increase their feelings of susceptibility when located in areas close to disasters. It could therefore be highlighted that GP affects PV and PS when the location is prone to disaster-related scenarios. Thus, it was hypothesized that:

H4: *GR has a significant direct effect on RC.*

H5: *GP has a significant direct effect on PS.*

H6: *GP has a significant direct effect on PV.*

The response of people towards a disaster may be accounted for. In the case of the study by Gumasing et al. [9], RC affects the behavioral aspect of a person. Mechler [33] indicated how RC should be considered upon creating a mitigation plan for disaster-related activities. To which, the behavioral aspects of people should be considered to attain higher response action. Covey et al. [22] expounded on highlighting individual differences, thus RC should be considered as a factor affecting different behaviors such as PB, SN, and AT. In addition, it was seen from the studies by Ong et al. [4] and Ong et al. [28] how these three variables under TPB highlight the action of an individual. Thus, the following were hypothesized:

H7: *RC has a significant direct effect on PB.*

H8: *RC has a significant direct effect on SN.*

H9: *RC has a significant direct effect on AT.*

PS and PV are key indicators under PMT which measures the motivation of an individual to protect themselves from disaster-related events. Westcott et al. [34] and Tang and Feng [35] explained how threat and coping appraisal of people affects individual behavior. To which, PS was indicated to affect PB, SN, and AT. The aim of people is to reduce the risk that may affect them or the people around them. Ong et al. [4] presented how PS and PV directly affect PB, SN, and AT—the integration section of PMT and TPB. It was highlighted that when PS is increased, these three factors would be affected in a directly proportional way. These relationships are similar to the studies presented by Prasetyo et al. [36], Ong et al. [28], and Kurata et al. [8]. Thus, it was hypothesized that:

H10: *PS has a significant direct effect on PB.*

H11: *PS has a significant direct effect on SN.*

H12: *PS has a significant direct effect on AT.*

H13: *PV has a significant direct effect on PB.*

H14: *PV has a significant direct effect on AT.*

Under TPB, three latent variables such as PB, SN, and AT were used. Ham et al. [37] showed how PB affects IP due to the ease or difficulty when behaviors are executed. Kahlor et al. [38] showed how individuals decide on positive self-control compared to the negative connotation of losing self-control. Moreover, Kahlor et al. [38] also showed that SN is one of the factors under information-seeking behavior in TPB. It is indicated in their study that SN precedes IP due to past experiences of people around an individual. To which, Lin et al. [39] showed how the environment the individual is in impacts evacuation and preparedness. AT towards risk perception in disaster-related events is positively connected to an individual's preventive measures [40]. In addition, Budhatoki et al. [41] showed how AT can be connected to the negative IP when preparedness before the event happens. Furthermore, different studies have presented how the three TPB latent variables significantly affect IP in disaster-related events [8,28,42]. Thus, the following were hypothesized:

H15: *PB has a significant direct effect on IP.*

H16: *SN has a significant direct effect on IP.*

H17: *AT has a significant direct effect on IP.*

3. Methodology

3.1. Participants

A total of 366 valid responses were collected through convenience sampling. Prior to answering the survey, the respondents were asked where they reside. Only those who resided in Chonburi Province were considered valid. Of 432 respondents, only 366 (85%) were considered acceptable. Using the Yamane Taro (Equation (1)) for acceptability of response number and in accordance with German et al. [43] and the National Research Council (US) Committee [44], a 90–95% confidence interval was utilized. The 90% confidence interval resulted in 100 respondents while 400 resulted for 95%. Taking the average of both, 250 respondents would suffice as a representation of the population from Chonburi Province [44,45], of which, a total of 366 responses were utilized in this study.

$$n = \frac{N}{1 + N\,e^2} \tag{1}$$

The collection of responses was gathered through different social media platforms due to the COVID-19 pandemic protocol. Following the suggestion of German et al. [43], the collected data may represent a generalized result through the utilization of SEM. The descriptive statistics of the respondents comprised of 48.1% male and 51.9% female with age groups around 15–23 years old (23.8%), 55–64 years old (23.0%), 45–54 years old (18.0%), 25–34 years old (16.4%), and 35–44 years old (15.8%) with the rest older than 65 years old, are presented in Table 1. In addition, the respondents have college graduate (56.8%), master's degree (15.6%), and senior high school (13.9%) education level. Moreover, the respondents have monthly salaries/allowances of less than THB 10,000 (24.9%), THB

20,001–30,000, more than THB 60,000 (16.1%), THB 30,001–40,000 (15.6%), and the rest are within THB 40,001–60,000. Lastly, most have fire insurance (52.2%) and 47.8% have none.

Table 1. Respondents' descriptive characteristics (n = 366).

Characteristics	Category	n	%
Gender	Male	176	48.1
	Female	190	51.9
Age	15–24 years old	87	23.8
	25–34 years old	60	16.4
	35–44 years old	58	15.8
	45–54 years old	66	18.0
	55–64 years old	84	23.0
	More than 64	11	3.00
Education	Junior High School	10	2.70
	Senior High School	51	13.9
	Technical–Vocation	32	8.70
	College	208	56.8
	Master's Degree	57	15.6
	PhD Degree	8	2.20
Monthly Salary/Allowance	Less than THB 10,000 Baht	91	24.9
	THB 10,001–20,000	51	13.9
	THB 20,001–30,000	59	16.1
	THB 30,001–40,000	57	15.6
	THB 40,001–50,000	26	7.10
	THB 50,001–60,000	31	8.50
	More than THB 60,000	51	13.9
Are you enrolled in fire insurance?	Yes	191	52.2
	No	175	47.8

3.2. Questionnaire

Table 2 presents the questionnaire utilized in this study. A total of 56 questions were considered as indicators for different latent variables considered in this study. The different indicators represent different latent variables such as fire perspective (FE), perceived severity (PS), response cost (RC), perceived vulnerability (PV), perceived behavioral control (PB), social norm (SN), attitude towards behavior (AT), geographic perspective (GP), and government response (GR) to measure intention to prepare (IP). A preliminary run was conducted to determine the validity of the questionnaire considered. Through a 5-point Likert scale survey, the initial result presented a 0.867 Cronbach's alpha value. Hair [45] indicated that a value greater than 0.70 would be considered valid, thus the questionnaire was deployed.

Table 2. Questionnaire.

Construct	Items	Measurement Items	References
Fire Perspective	FE1	I think workplaces and houses should prepare for fire and smoke control protocols.	Kurata et al. [8]
	FE2	I think workplaces and houses should have fire alarms.	Kurata et al. [8]
	FE3	I think workplaces and houses should preparing for fire evacuation plans.	Kurata et al. [8]
	FE4	I think workplaces and houses should preparing for fire safety policies.	Kurata et al. [8]
	FE5	I think workplaces and houses should holding fire insurance policies.	Kurata et al. [8]
	FE6	I think workplaces and houses should preparing for fire precautions system.	Kurata et al. [8]

Table 2. *Cont.*

Construct	Items	Measurement Items	References
Geographic Perspective	GP1	I think the government should classify fire risk areas.	Kuhlicke et al. [31]
	GP2	I think the government should monitor the risky areas.	Kuhlicke et al. [31]
	GP3	I think the government should manage the control on fuel consumption and usage.	Kuhlicke et al. [31]
	GP4	I think that wildlife is a serious threat that may cause fire.	Kuhlicke et al. [31]
Government Response	GR1	I think the government should pay remediation for fire victims.	Kurata et al. [8]
	GR2	I think the government should establish a fire foundation.	Kurata et al. [8]
	GR3	I think the government should practice fire evacuation plans.	Kurata et al. [8]
	GR4	I think the government should managing policies on renewable energy, fossil fuels, and coal.	Kurata et al. [8]
	GR5	I think the government should establish reforestation campaigns for response as emission reduction.	Kurata et al. [8]
Perceived Severity	PS1	I find fire as a serious hazard which causes accident.	Ong et al. [4]
	PS2	I find that fires can lead to property lost.	Ong et al. [4]
	PS3	I find that fire can lead to serious injuries.	Ong et al. [4]
	PS4	I find that fire causes severe danger compared to other accidents.	Ong et al. [4]
	PS5	I think sanction against breach of fire regulations are important.	Ong et al. [4]
Perceived Vulnerability	PV1	I think I am vulnerable to fire.	Prasetyo et al. [36]
	PV2	I think my area is very vulnerable to fire.	Prasetyo et al. [36]
	PV3	I think my family is vulnerable to fire.	Prasetyo et al. [36]
	PV4	I think my friends are vulnerable to fire.	Prasetyo et al. [36]
Response Cost	RC1	I think we should fine sanction against breach of fire regulations.	Gumasing et al. [9]
	RC2	I think we should claim loss fee from fire insurance companies.	Gumasing et al. [9]
	RC3	I think we should pay remediation for fire victims.	Gumasing et al. [9]
Perceived Behavioral Control	PB1	I can find the fire alarm and push it when needed.	Ong et al. [4]
	PB2	I can call emergency numbers to report fire incidents.	Ong et al. [4]
	PB3	I can perform first aid to others if they are injured.	Ong et al. [4]
	PB4	I can find fire extinguishers in my workplace.	Ong et al. [4]
	PB5	I can soak my handkerchief and cover my nose when there is fire.	Ong et al. [4]
	PB6	I think I can mitigate immediately the fire in my area.	Ong et al. [4]
	PB7	I can control myself and perform low crawl on knees to find an emergency exit.	Ong et al. [4]
	PB8	I will use a ladder instead of an elevator when fire happens.	Ong et al. [4]
	PB9	I can evacuate from fire accidents.	Ong et al. [4]

Table 2. *Cont.*

Construct	Items	Measurement Items	References
Subjective Norm	SN1	I think people in the industrial estate is likely to have fire hazards.	Prasetyo et al. [36]
	SN2	I think my family is highly likely to feel fire hazards.	Prasetyo et al. [36]
	SN3	I think my role and status is likely to influence fire hazards.	Prasetyo et al. [36]
	SN4	I think my workplace is likely to cause fire hazards.	Kurata et al. [8]
	SN5	I think my lifestyle is likely to influence fire hazards.	Kurata et al. [8]
	SN6	People around me think that I should prepare for fire hazards.	Kurata et al. [8]
	SN7	I feel that people important to me think that I should prepare for fire hazards.	Ong et al. [28]
	SN8	My family influenced me to think that I should prepare for fire hazards.	Ong et al. [28]
	SN9	The government influenced me to think that I should prepare for fire hazards.	Ong et al. [28]
Attitude Towards Behavior	AT1	I feel fire is a danger to the community.	Kurata et al. [8]
	AT2	I feel fire is a danger to wildlife.	Kurata et al. [8]
	AT3	I feel fire is a danger to people and properties.	Kurata et al. [8]
	AT4	I feel people in community are not aware of the fire.	Kurata et al. [8]
Intention to Prepare	IP1	I prefer not to use old electronic appliances to prevent fires.	Ong et al. [4]
	IP2	I keep chemical substances in their own places to prevent fire.	Ong et al. [4]
	IP3	I maintain circuits and electronic system to prevent fires.	Ong et al. [4]
	IP4	I keep oils away from electronic sources to prevent fires.	Ong et al. [4]
	IP5	I keep fuels away from electronic sources to prevent fires.	Ong et al. [4]
	IP6	I keep children away from electronic sources to prevent fires.	Ong et al. [4]
	IP7	I turn off electronic sources when not in use to prevent fires.	Ong et al. [4]

Upon data collection, the Harman's single factor test was employed to test the common method bias. It was indicated that the threshold should be less than 50% in order that no CMB would be detected [4,8]. In this case, a 26.32% value was obtained which indicated no CMB. On the other hand, the dataset was tested for normality using the Shapiro–Wilk test. The resulting value was within ± 1.96 which indicated that the collected data are normal [4].

3.3. Structural Equation Modeling

SEM has a number of advantages over traditional data-analytic methods such as multiple linear regression, correlation analysis, logistic regression, etc. [45]. Researchers can assess the effects of theoretical or speculative constructs, sometimes known as "latent variables" [46]. SEM offers a comprehensive statistical approach for testing current observed and latent variables [47]. SEM constructs ten latent variables: fire perspective, perceived severity, response cost, perceived vulnerability, perceived behavioral control, social norm, attitude towards behavior, geographic perspective, government response, and intention to prepare. Compared to other statistical tools mentioned, the SEM analysis covers the regression and multiple linear regression due to its ability to assess the causal relationships of direct, indirect, and total effects [45]. With that, SEM is widely utilized nowadays. However, several studies have criticized SEM as a sole methodology [23–25], especially its limitations. Thus, Duarte and Pinho [25] suggested integrating other tools to justify and highlight significant latent variables for the analysis. Thus, this study considered SEM with ANN.

3.4. Artificial Neural Network

For a total of 20,496 datasets, initial optimization was run using Python 5.1. A training and testing ratio of 80:20 was utilized. The feed-forward ANN process was employed following the study by Ong et al. [48]. The pseudocode is presented, which is similar to the GitHub ANN repository [49]. Prior to running the optimization process, data cleaning using correlation analysis was conducted considering a p-value of 0.05. Anything greater than that would be considered insignificant. In addition, a correlation coefficient of less than 0.20 was considered to be insignificant. Following the suggestion of Pradhan and Lee [50], 10 runs per combination were conducted with 150 epochs each [51]. A 92.37% accuracy from the average test was presented from Elu as the activation function for the hidden layer, Sigmoid for the output layer, and Adam as the optimizer. Moreover, 50 nodes were utilized in the hidden layer and IP represented the output node.

ANN Pseudocode:

Step 1. Loading of preprocessed data.

Step 2. Feature selection was set for dependent and independent variables.

Step 3. Setting and splitting the dataset among training and testing utilizing train_test_split from sklearn.model_selection with 0 random state.

Step 4. Utilizing Keras sequential for the number of nodes and parameters for the input layer, hidden layer, and output layer.

Step 6. Setting parameters for optimizer and number of epochs.

Step 7. Feedforward process (learning rate, bias, weight (w)) considers the Equation (2),

$$Y = \sum_{i=1}^{m} (x_i * w_i) + b \tag{2}$$

where:

x_i = input features

w_i = weights

b = bias

Then the activation function (*f*(Y)) is applied for the output, $output = f(Y)$.

The calculation pseudocode is as follows:

```
OutputB = 1st input*w[0] + 2nd input*w[1] + bias*w[2]
If OutputB > 0: #Activation Function considered
    OutputB = 1
Else
    OutputB = 0
Error = output – OutputB
W[0] += error * 1st input * learning rate
W[1] += error * 2nd input * learning rate
W[2] += error * bias * learning rate
OutputB = #calculation using the activation function
```

Step 8. Printing of validation test results. Generation of training and testing accuracy result, precision, recall values, loss rate, and run time will be obtained.

4. Results

4.1. Structural Equation Modeling Results

The initial SEM to predict factors affecting the intention to prepare for the mitigation of fire in Chonburi Province, Thailand, is represented in Figure 2. Following the suggestion of Ong et al. [48] and Chuenyindee et al. [52], indicators with values less than 0.50 would be removed to enhance the model fit of the framework. In addition, p-values greater than 0.05 were removed as they were deemed insignificant [45]. It could be seen from the model that GP on PV and FP on PV, PS on PB and PV on AT were removed due to their p-value. In addition, AT4 was removed with an indicator value of less than 0.50.

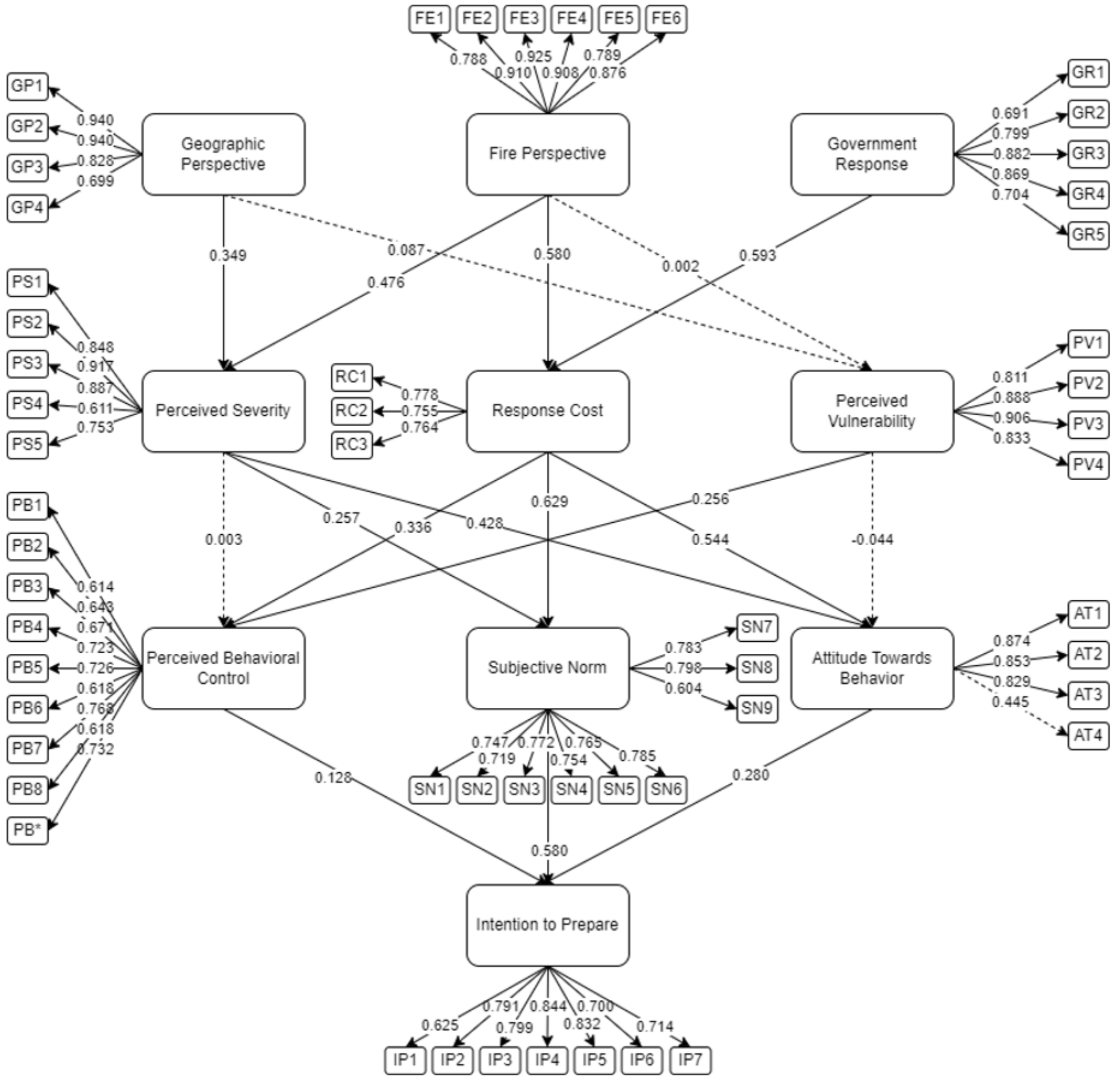

Figure 2. The initial SEM to determine factors affecting intention to prepare for fire mitigation.

After the removal of insignificant relationships and indicators, the model was run to enhance the model fit [38]. Of 17 hypotheses, 13 were considered to be significant. H3, H6, H10, and H14 had *p*-values greater than 0.05. The final SEM for measuring intention to prepare for the mitigation of fire disaster in Chonburi Province, Thailand, is presented in Figure 3.

The descriptive statistics of the indicators of the initial and final factor loading are presented in Table 3. It could be seen that all factors are within the threshold (>0.50) and are considered acceptable. In addition, Table 4 represents the model fit considered in this study. From the results, all parameters were within the threshold set by Gefen et al. [53] and Steiger [54]. The IFI, CFI, TLI, GFI, and AGFI are considered acceptable values greater than 0.80. Moreover, an RMSEA value of less than 0.07 would be considered acceptable. Therefore, it could be stated that the constructs and model are highly acceptable.

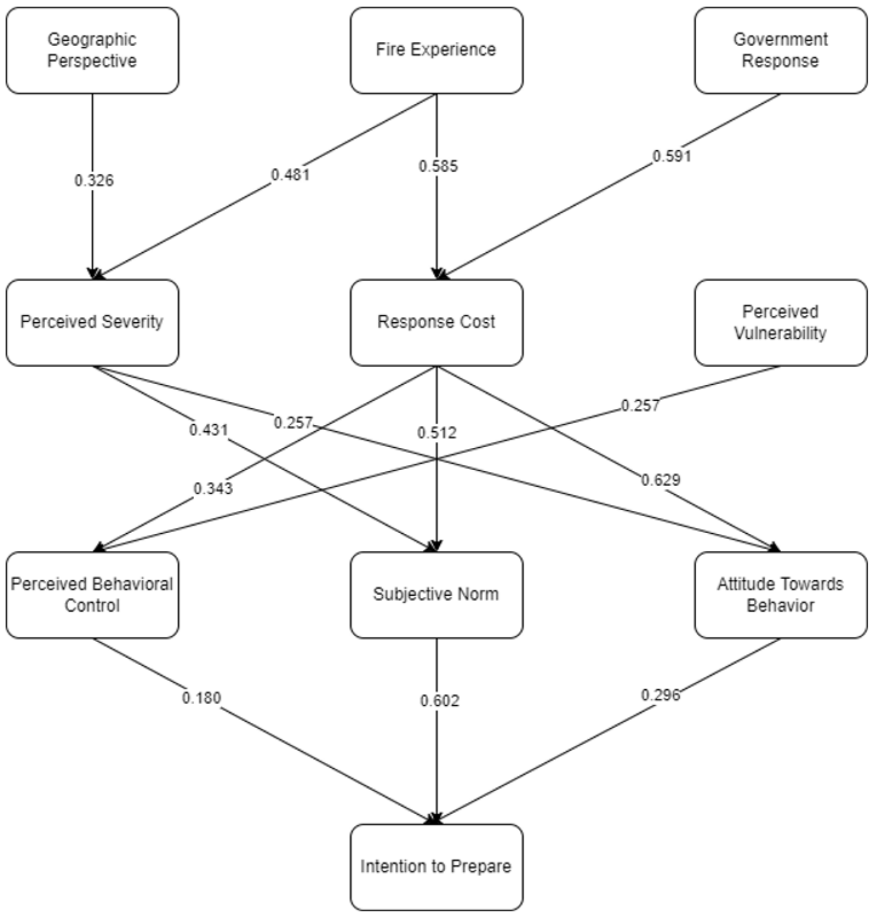

Figure 3. The final SEM to determine factors affecting intention to prepare for fire mitigation.

Table 3. Indicators statistical analysis.

Variable	Item	Mean	StD	Factor Loading	
				Initial	Final
Fire Perspective	FE1	4.5000	0.79983	0.788	0.788
	FE2	4.5874	0.77760	0.910	0.910
	FE3	4.5656	0.77270	0.925	0.924
	FE4	4.5519	0.76304	0.908	0.908
	FE5	4.4290	0.82703	0.789	0.789
	FE6	4.6311	0.68886	0.876	0.876
Geographic Perspective	GP1	4.3470	0.81582	0.940	0.940
	GP2	4.3634	0.81874	0.940	0.941
	GP3	4.3852	0.83859	0.828	0.828
	GP4	4.4454	0.77708	0.699	0.699
Government Response	GR1	4.3060	0.88477	0.691	0.690
	GR2	4.2923	0.91520	0.799	0.798
	GR3	4.3743	0.80362	0.882	0.882
	GR4	4.4098	0.81177	0.869	0.869
	GR5	4.3634	0.88002	0.704	0.704
Perceived Severity	PS1	4.6475	0.73565	0.848	0.854
	PS2	4.7077	0.69384	0.917	0.932
	PS3	4.6503	0.73510	0.887	0.890
	PS4	4.2131	0.89653	0.611	0.587
	PS5	4.4071	0.79094	0.678	0.661

Table 3. *Cont.*

Variable	Item	Mean	StD	Factor Loading	
				Initial	**Final**
Perceived Vulnerability	PV1	2.5820	1.08165	0.811	0.809
	PV2	2.4399	1.09065	0.888	0.896
	PV3	2.4016	1.07520	0.906	0.908
	PV4	2.5164	1.06938	0.833	0.829
Response Cost	RC1	4.4536	0.74523	0.778	0.778
	RC2	4.4645	0.78520	0.755	0.757
	RC3	4.5355	0.75315	0.764	0.764
Perceived Behavioral Control	PB1	3.2104	1.25272	0.614	0.615
	PB2	3.4590	1.22406	0.643	0.644
	PB3	2.8115	1.08032	0.671	0.672
	PB4	3.4973	1.28372	0.723	0.724
	PB5	3.8825	1.12011	0.726	0.727
	PB6	2.6066	1.15075	0.618	0.619
	PB7	3.3989	1.10262	0.768	0.769
	PB8	4.2814	1.00956	0.618	0.619
	PB9	3.6913	1.03911	0.732	0.733
Subjective Norm	SN1	4.5847	0.66801	0.747	0.753
	SN2	4.3470	0.82915	0.719	0.717
	SN3	4.5082	0.73926	0.772	0.773
	SN4	4.3497	0.82634	0.754	0.749
	SN5	4.4781	0.80974	0.765	0.766
	SN6	4.4208	0.81628	0.785	0.786
	SN7	4.4754	0.77862	0.783	0.785
	SN8	4.5137	0.74656	0.798	0.799
	SN9	4.0874	0.96117	0.604	0.598
Attitude Towards Behavior	AT1	4.6093	0.74966	0.874	0.905
	AT2	4.5956	0.76239	0.853	0.871
	AT3	4.6940	0.65318	0.829	0.816
	AT4	4.0574	0.89104	0.445	-
Intention to Prepare	IP1	4.0137	1.05847	0.625	0.614
	IP2	4.3115	0.84479	0.791	0.790
	IP3	4.4016	0.77981	0.799	0.804
	IP4	4.3470	0.86789	0.844	0.849
	IP5	4.3852	0.80865	0.832	0.839
	IP6	4.0765	0.96494	0.700	0.695
	IP7	4.3415	0.84450	0.714	0.716

Table 4. Model fit.

Goodness of Fit Measures of SEM	Parameter Estimates	Minimum Cut-Off	Suggested by
Incremental Fit Index (IFI)	0.896	>0.80	Gefen et al. [53]
Tucker–Lewis Index (TLI)	0.887	>0.80	Gefen et al. [53]
Comparative Fit Index (CFI)	0.895	>0.80	Gefen et al. [53]
Goodness of Fit Index (GFI)	0.860	>0.80	Gefen et al. [53]
Adjusted Goodness of Fit Index (AGFI)	0.833	>0.80	Gefen et al. [53]
Root Mean Square Error (RMSEA)	0.060	<0.07	Steiger [54]

Table 5 presents the causal relationship of the framework created. From the direct effects, RC was seen to have the highest significant effect, followed by SN, GR, FE, PS, GP, PV, AT, and PB. Further relationship verification was conducted utilizing ANN.

Table 5. Direct, indirect, and total effects.

No	Variable	Direct Effect	*p*-Value	Indirect Effect	*p*-Value	Total Effect	*p*-Value
1	GR → RC	0.591	0.005	-	-	0.591	0.005
2	FE → RC	0.585	0.023	-	-	0.585	0.023
3	FE → PS	0.481	0.006	-	-	0.481	0.006
4	GP → PS	0.326	0.009	-	-	0.326	0.009
5	PV → PB	0.257	0.004	-	-	0.257	0.004
6	RC → PB	0.343	0.009	-	-	0.343	0.009
7	RC → SN	0.512	0.013	-	-	0.512	0.013
8	RC → AT	0.629	0.005	-	-	0.629	0.005
9	PS → SN	0.431	0.013	-	-	0.431	0.013
10	PS → AT	0.257	0.021	-	-	0.257	0.021
11	PB → IP	0.180	0.043	-	-	0.180	0.043
12	SN → IP	0.602	0.009	-	-	0.602	0.009
13	AT → IP	0.296	0.042	-	-	0.296	0.042
14	GR → PB	-	-	0.203	0.003	0.203	0.003
15	GR → AT	-	-	0.303	0.003	0.303	0.003
16	GR → SN	-	-	0.371	0.005	0.371	0.005
17	GR → IP	-	-	0.270	0.007	0.270	0.007
18	FE → PB	-	-	0.201	0.012	0.201	0.012
19	FE → AT	-	-	0.507	0.011	0.507	0.011
20	FE → SN	-	-	0.491	0.011	0.491	0.011
21	FE → IP	-	-	0.363	0.018	0.363	0.018
22	GP → AT	-	-	0.140	0.003	0.140	0.003
23	GP → SN	-	-	0.084	0.002	0.084	0.002
24	GP → IP	-	-	0.065	0.002	0.065	0.002
25	PV → IP	-	-	0.020	0.014	0.020	0.014
26	PS → IP	-	-	0.198	0.019	0.198	0.019

4.2. Artificial Neural Network Results

Figure 4 represents the ANN model utilized in this study. From the results, GP was seen to be the highest and most important factor affecting IP, followed by SN, FE, PS, AT, RC, PB, GR, and PV. The model created utilized the optimized parameters of Elu and Sigmoid for the activation function of hidden and output layers, respectively. In addition, the Adam optimizer and 80:20 training testing ratio were utilized for the final optimization. The data was run using 200 epochs and the average testing resulted in an average result of 94.82%.

The scores of independent variable importance for ANN to verify the results are presented in Table 6. It was seen that GP had the highest score of importance affecting IP for the mitigation of fire in Chonburi Province, Thailand, followed by SN, FE, PS, AT, RC, PB, GR, and the least important was PB. It was seen from both SEM-ANN hybrid results that all factors were significant, however, they presented different levels. This confirms the claim of both Woody [23] and Fan et al. [24] that mediation and indirect effects affected the variable significance level in SEM. Thus, the ANN sequence with SEM results will be the flow of the discussion of results for mitigation to prepare for the fire disaster in Chonburi Province, Thailand.

Table 6. Independent variable importance score ANN.

Variables	Importance	Normalized Importance
Geographic Perspective	0.221	100
Subjective Norm	0.203	92.3
Fire Experience	0.200	91.8
Perceived Severity	0.194	87.6
Attitude Towards Behavior	0.188	85.2
Response Cost	0.484	83.4
Perceived Behavioral Control	0.170	76.9
Government Response	0.167	75.7
Perceived Vulnerability	0.109	49.3

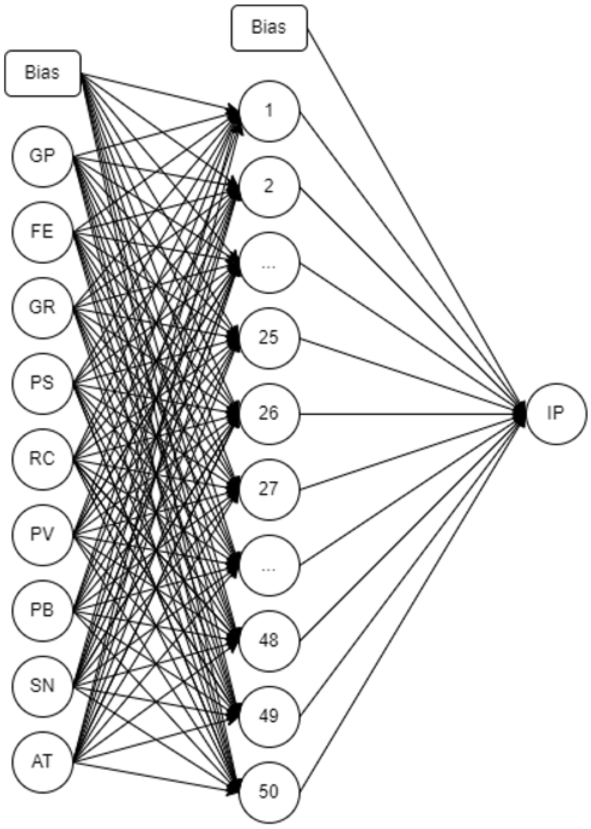

Figure 4. Artificial neural network model.

5. Discussion

Evident fire disaster has been seen to be present in the Chonburi Province in Thailand. The need to assess factors affecting the intention to prepare for a fire disaster should be explored. This study utilized the SEM-ANN hybrid to test the hypotheses created and predict factors affecting intention to prepare (IP) for fire disaster with factors under PMT and TPB. Several factors such as fire perspective (FE), perceived severity (PS), response cost (RC), perceived vulnerability (PV), perceived behavioral control (PB), social norm (SN), attitude towards behavior (AT), geographic perspective (GP), and government response (GR) were assessed simultaneously.

From the results, GP was seen to be the most significant factor (100%). The SEM results presented a direct effect on PS (β: 0.326; $p = 0.009$) and an indirect effect on IP (β: 0.065; $p = 0.002$). The respondents think that the government should classify and monitor fire risks, manage and monitor fuel consumption, and consider wildlife that may cause fire disasters. GP is an important factor affecting IP because the location of a person affects how severe the impact of a disaster would be [8]. The more susceptible the location of an individual is to a disaster, the more likely they will prepare for it [9]. Accordingly, Bronfman et al. [55] highlighted how people in Chile would consider the more negative effects of disaster when dealing with IP. Similar to the study of Shi et al. [56], people in China would consider positive and high IP when presented with high negative effect of disasters.

Second, SN was seen to directly affect IP. The SEM result suggested that SN has a highly significant direct effect on IP (β: 0.602; $p = 0.009$) and is the second-highest important factor (92.3%). The influence of industries was indicated to have an effect on fire disaster, people around the individual were said to be affected by fire disaster, and the workplace and lifestyle of an individual were seen to be indicators of this factor. Kusumastuti et al. [57] confirm the claim that SN is a significant factor affecting IP. People would respond to a disaster when people that are important to them would be affected as well. This leads to a motivation to increase IP [38] upon dealing with how people are living day to day. Similar results were also found for people living in the Philippines [4,8].

Third, FE is a significant factor affecting IP (91.8%). The indicators show how the workplace and household should prepare for fire disaster based on experience, create evacuation plans, have insurance for fire disaster, and consider the installation of smoke and fire alarms. This has led to a direct significant effect on RC (β: 0.585; p = 0.023) and PB (β: 0.481; p = 0.006), with an indirect effect on IP (β: 0.363; p = 0.018). Shen et al. [58] showed how different experiences and behavior of people would lead to an act not similar to other individuals. Similarly, Gumasing et al. [9] showed how the knowledge and understanding of people would increase their perception of the severity of a disaster, leading to an increase in their IP. Kurata et al. [8] also presented similar findings when people's experiences would increase their alertness and preparation for the mitigation of disasters.

Fourth, PS was seen to be an important factor affecting IP (87.6%). The indicators considered constructs such as the serious hazard of fires, loss of property, and injuries; people perceive fire as more dangerous than other disasters, and should have sanction among people that breach fire regulations. This has led to direct effects on people's behaviors such as SN (β: 0.431; p = 0.013) and AT (β: 0.257; p = 0.021) with an indirect effect on IP (β: 0.198; p = 0.0019). This is supported by the results of the study by Bollettino et al. [59]. The increased awareness and knowledge of a disaster would also increase people's IP. Taking into consideration available resources and information would lead to knowing PS, which will increase the motivation for IP [60]. It could be stated that PS is directly proportional to IP when dealing with disasters [4].

Fifth, AT directly and significantly affected IP (β: 0.296; p = 0.042). The indicators presented the significant results of how people perceive fire as a danger to the community, wildlife, people and properties, and that people in the community are not aware of the fire. This led to a high score of importance for AT (85.2%). Ong et al. [4] showed the increase in IP when people perceive the heightened level of danger from disasters. The way other people would feel and act would affect the attitude of an individual to act the same way. In this case, if the perceived danger is within the surroundings, then people would have a positive AT affecting IP. As support, Song and Shi [61] explained how AT is affected by societal pressure and the evident effect of fire on their surroundings. AT was indicated to be an important factor greatly affecting an individual's IP [62].

Six, RC had an importance score of 83.4%, which directly affects IP. To which, a direct effect on the TPB latent variables of PB (β: 0.343; p = 0.009), SN (β: 0.512; p = 0.013), and AT (β: 0.629; p = 0.005) were seen. It was shown that people believe that filing sanctions, claiming fire insurance loss fees, and paying remediation for fire victims should be in place. The increase in stress due to RC has been evident across countries [7,63]. The increase in the number of disasters in Oceania also increased RC [58]. In addition, the increase of disasters in the Philippines increased RC as well [7,9]. Gumasing et al. [9] highlighted that RC would lead to a positive significant effect on different behaviors of individuals when investment in risk reduction is not applied. These findings justified the results presented.

Seventh, PB was shown as the least important but significant factor affecting IP (β: 0.180; p = 0.043). It was indicated that people know where fire alarms and extinguishers are, know emergency contacts, can perform first aid, know what to do when there is fire, believe they can mitigate fire disaster when it happens, and can evacuate easily when there is fire. This explains why PB has a low score of importance (76.9%) due to people believing they can manage fire if it occurs. Mondino et al. [64] explained how people with prior experience and knowledge of a certain disaster know what to do when it occurs again. Individuals with details and particulars of a disaster such as fire, result in their willingness and positive behavior to prepare and mitigate it happening negatively [65,66].

Eighth, GR proved to be an important and significant factor affecting IP (75.7%), with a direct significant effect on RC (β: 0.519; p = 0.005). Indicators presented constructs such as the government having to pay remediation, establish fire foundations, practice evacuation plans, manage policies, and establish reforestation campaigns. Following the study of

Kurata et al. [8], GR was shown to have a low significance level as well. Their study highlighted how retroactive governance would lead to an increase in people's behavior to prepare and mitigate disasters. Moreover, Gumasing et al. [9] and Ong et al. [4] explained how the impact of the government on creating policies and plans would increase the factor affecting citizens' intentions to prepare for the mitigation of disasters such as fires.

Lastly, PV affected IP significantly (indirect β: 0.020; $p = 0.014$). People think they are vulnerable to fire, their location, family, and friends were also indicated as vulnerable. Thus, a direct significant effect on PB (β: 0.257; $p = 0.004$) was seen. Seeing how people believe they can control their actions and know what to do when a disaster occurs led to the lowest score of importance for this factor (49.3%). Similar to the study by Kurata et al. [8], PV was considered to have a low-significance effect on people's behavior. However, Kusumastuti et al. [57] showed that despite the low significance, people will still proactively take action to reduce the negative impact of a disaster. Moreover, Weichselgartner and Pigeon [67] showed how knowledge and experience of a disaster would lead to low PV, but would result in gaining more information to understand disaster risks and mitigation. Thus, supporting the findings of this study.

Interestingly, it was seen from the IP indicators that people would not prefer to use old electronic appliances to prevent fires, mitigated by placing chemical substances in designated areas, maintain electronic and circuit systems, keep oils, fuels, and children away from electronics, and turn off power sources when not in use. From the findings, it could therefore be deduced that people are aware of their location being prone to fire disasters, people around and important to them are vulnerable to the disaster, and experiences due to the constant number of fires happening in the area would lead to urgency to prepare for mitigation of the fire disaster.

5.1. Theoretical and Practical Contribution

The evident results showed how the extended integrated framework of PMT and TPB could be utilized as a framework to measure people's intention to prepare for the mitigation of disasters. The contribution of extending factors such as government response and geographic location were important since the consideration of specific areas of study was seen to be prone to fire disaster. Thus, this study posits that when dealing with specific disaster-prone areas, these factors may be included. Moreover, the implementation of the SEM and ANN hybrid led to more substantial findings for factors influencing human behavior. It could therefore be suggested to include machine learning tools with SEM to help resolve the disadvantage and flaws of the single tool alone.

Based on the findings of this study, the government would play a significant role in reducing response cost, perceived severity, and perceived vulnerability among citizens. Thus, the findings of this study could be utilized by the government sector to create mitigation plans to reduce the severity of disasters such as fire. Moreover, the government may capitalize on the findings of this study to promote the intention of people to reduce, mitigate, and prepare for any disasters that may occur. The findings of this study could also be applied and extended by other researchers dealing with disasters in different countries. Lastly, the framework and methodology of this study may be utilized for studies dealing with human behavior worldwide.

5.2. Limitations and Future Research

Despite the strong and significant findings of this study, several limitations could still be considered. First, though sufficient, this study was only able to consider a few respondents to be generalized. Second, only an online self-administered cross-sectional survey was utilized in this study. It is suggested to consider more respondents, distributed among the more diverse age groups, and even consider interviews. This way, more factors and findings may substantiate lacking information that may not be found in the paper. Third, only the SEM-ANN hybrid was utilized to confirm the findings. It is suggested that future researchers may create clustering methods such as particle swarm optimization and fuzzy clustering to determine similar indicators affecting human behavior such as intention to prepare. Lastly, it is also suggested to consider different employment statuses and marital status to highlight significant differences among factors affecting the intention to prepare when it comes to ownership of property and dependence.

6. Conclusions

The evident negative effect of man-made fire as a disaster has been seen worldwide. This has led to a constant or increased amount of damage and even death in different countries. One of the regions that suffer consistent fire disaster is Chonburi Province in Thailand. However, despite the presence of a number of fire disasters in Thailand [68–73], this has been considered underexplored. This study aimed to predict factors affecting the behavioral intention to prepare for the mitigation of man-made fire disasters in Chonburi Province, Thailand.

Several factors under the integrated and extended protection motivation theory and theory of planned behavior were considered in this study. Factors such as geographic perspective, fire perspective, government response, perceived severity, response cost, perceived vulnerability, perceived behavioral control, subjective norm, and attitude were evaluated simultaneously to measure intention to prepare for fire disaster in Chonburi Province, Thailand. A structural equation modeling and artificial neural network hybrid approach were utilized in this study to evaluate 20,496 datasets collected from 366 respondents. Through an online self-administered cross-sectional survey, the response was collected through convenience sampling to represent the generalized results presented.

The results indicated how geographic location, subjective norm, fire experience, and perceived severity were significantly evident and important factors affecting the intention to prepare. It was seen that people with knowledge would consider the level of severity of a disaster based on experience. In addition, the effect on the community and people that are important to an individual would heighten their behavior and attitude for intention to prepare for mitigation of fire disaster. Moreover, the geographic location was seen to be the most important factor contributing to intention to prepare. Since the Chonburi Province has been repeatedly struck with fire disasters, it explains how the geographic location is considered the most important factor affecting intention. In order to increase the level of intention among people, it was deduced that the government should implement mitigation plans, create protocols and policies, and even give sanctions to promote and mitigate fire disasters in the area. To which, government response and response cost were also considered significant factors.

The findings and results of this study may contribute to the government sector in creating plans to protect citizens in the Chonburi Province region in Thailand. In addition, the results presented may be considered by other researchers to strengthen findings of human behavior in relation to natural disaster preparedness. The framework and methodology considered in this study may be applied and extended to measure human behavior studies, not only in natural disasters. Moreover, the application of the SEM-ANN hybrid may be considered by health-related and behavioral researchers worldwide.

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