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Classification modeling of intention to donate for victims of Typhoon Odette using deep learning neural network

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ABSTRACT

The need for stability in the economy for world development has been a challenge due to the COVID-19 pandemic. In addition, the increase of natural disasters and their aftermath have been increasing causing damages to infrastructure, the economy, livelihood, and lives in general. This study aimed to determine factors affecting the intention to donate for victims of Typhoon Odette, a recent super typhoon that hit the Philippines leading to affect 38 out of 81 provinces of the most natural disaster-prone countries. Determining the most significant factor affecting the intention to donate may help in increasing the engagement of donations among other people to help establish a more stable economy to heighten world development. With the use of deep learning neural network, a 97.12% accuracy was obtained for the classification model. It could be deduced that when donors understand and perceive both severity and vulnerability to be massive and highly damaging, then a more positive intention to donate to victims of typhoons will be observed. In addition, the influence of other people, the holiday season when the typhoon happened, and the media as a platform have greatly contributed to heightening the intention to donate and control over the donor's behavior. The findings of this study could be applied and utilized by government agencies and donation platforms to help engage and promote communication among donors. Moreover, the framework and methodology considered in this study may be extended to evaluate intention, natural disasters, and behavioral studies worldwide.

1. Introduction

Natural disasters and natural calamities have been increasing and evidently, the last decade consistently produced significant disasters globally. Presented in Fig. 1 is the annual number (2017–2021) of natural disaster events that happened globally

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(Jaganmohan, 2022). As of 2022, the Emergency Event Database recorded 432 natural disasters which caused 10,492 deaths and 101.8 million people were affected (OCHA, 2022). Globally, OCHA (2022) reported a total economic loss of 112.5 billion USD. It was also reported that Asian countries have been impacted severely where 40% of the natural disaster happened. The Philippines, among all Asian countries, have been a center for natural disasters even during the early periods (Kurata et al., 2022).

The increase in natural disasters affected a lot of people. This motivated the government, philanthropists, and researchers to look for ways to help with the aftermath of these unfortunate events. Titl et al. (2021) presented that government spending and resource allocation has been a major concern and the allocation of funds is distorted. In the Philippines, Kurata et al. (2022) presented that government response to natural disasters has been lacking. Therefore, the need for donations across different sectors has been subjected to the most effective measures to help mitigate aftermaths caused by natural disasters, especially in the third world and developing countries. One of the platforms available is UNICEF whose goal is to help communities with limited access to education, nutrition and health, protection, decent shelter, and vulnerability.

UNICEF enables the movement toward world development in different aspects, such as donations for natural disasters. It has reached several media users through the promotion set in social media platforms, websites, and even traditional pamphlets. However, the need to increase the number of donors and amount of donation has been widely advertised. Recently, available platforms for an earthquake in Afghanistan and relief operations for affected people are available. Nonetheless, victims of Typhoon Odette are still in need of donations despite the available help given. The Philippines is considered as one of the countries that usually need help when it comes to natural disaster aftermath. The help obtained will assist these developing countries that contribute toward different aspects of the world. Taking the Philippines for example, Ong (2022) stated that they are the center for trades and widely recruited healthcare professionals. However, being a center for natural disasters, the need to help the country has been heard throughout the world.

One of the major natural disasters which raised global donations is Typhoon Odette (Rai) which happened in the Philippines, late 2021. Typhoon Odette affected infrastructures (approximately 73 million USD), and agriculture (approximately 36.5 million USD), and almost 4 million people with 108,000 houses and property damages. This natural disaster has been categorized as equivalent to five super typhoons. Thirty-eight (38) of 81 provinces in the Philippines were affected (Luna, 2021; OCHA, 2021). Gomez (2021) also highlighted how the lack of supplies, assistance, and funds has left individuals to suffer from illnesses such as dehydration, diarrhea, injuries, hunger, some even led to deaths. To help, the Center for Disaster Philanthropy (2021) established a platform that would gather assistance and donations for the victims, which would eventually lower the effect of the aftermath (Righi et al., 2021). An immense amount of donations is deemed needed to restore damages of the provinces that were greatly affected by the typhoon.

Several studies have only focused on preparation, mitigation, and intention among people before, during, and after a natural disaster. No studies regarding the intention to help, donate, or anything related were made in relation to natural disaster aftermath. Bollettino et al. (2020) considered Filipino perception of climate change and their preparedness for natural disasters. Venable et al. (2021) focused on the risk perception of typhoon natural disasters. Similarly, the intention to prepare for natural disasters for earthquakes (Ong et al., 2021), volcanic eruptions (Kurata et al., 2022b), the perceived effectiveness of flood disaster response (Kurata et al., 2022), the effectiveness of community quarantine (Prasetyo et al., 2020), and typhoon response efficacy (Gumasing et al., 2022) were considered. Despite significant findings and relevant inputs, the mitigation, preparation, and intention for a natural disaster will not suffice when a significant effect of natural disaster aftermath happens. Thus, the need to investigate outside help among donors should be evaluated to cater to the different needs in the event of major disasters. The proper and effective promotion would raise enough value to help during major natural disasters.

As presented, typical human factors and human behavior-related studies covering natural disaster-related literatures have considered the use of structural equation modeling (SEM). However, several studies have debated its capabilities for complex model structures. SEM is highly utilized for linear relationship determination (Henderson and Follett, 2020). Henderson and Follett (2020) considered the comparison between Bayesian stochastic frontier analysis (BSFA) and SEM for human capabilities. It was seen that

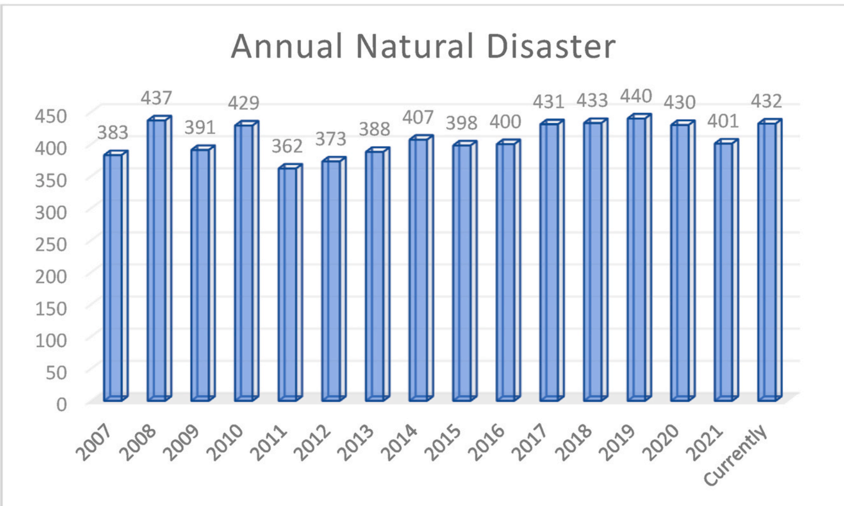

Fig. 1. Annual natural disaster events.

BSFA outperformed SEM in any case. In the study by Woody (2011), it was presented how mediating latent variables greatly affected the results of significant levels. This was supported by Fan et al. (2016) which included an explanation of the distance of latent variables from the dependent variable. The farther the independent factors are, the lower the significance level. Therefore, several studies have considered a SEM-Neural Network hybrid to deduce efficient results from the limitations of SEM.

Neural networks performed from algorithms mimic how the neurons of the human body transfer information to the brain (Kengpol and Wangananon, 2006). The signal transfer is structured as the hidden layers of the neural network (Jahangir et al., 2019). It was explained in the study of Yuduang et al. (2022) that more hidden layers require more complex calculations correlating to the complexity of the framework. Several studies have considered neural networks in deciphering the factors affecting human behavior. Ong et al. (2022b) considered the random forest classifier and deep neural networks to analyze factors that affected the perceived effectiveness of a COVID-19 contact tracing mobile application. It was seen that with the presence of multiple mediating factors, more hidden layers are considered for complex calculation. Different studies such as Liébana-Cabanillas et al. (2017) and Kalinić et al. (2021) considered satisfaction and acceptance using neural networks to evaluate human behavior. In addition, Kheirollahpour et al. (2020) presented the advantage of using neural networks to analyze nonlinear relationship frameworks with higher efficiency compared to traditional statistical treatment and multivariate tools.

As explained by Jamshidi et al. (2022), neural networks can easily analyze and predict patterns of nonlinear relationships based on framework, complexity, and even uncertain output based on datasets. In this manner, it was indicated by German et al. (2022) how neural networks, in this case deep learning, calculate patterns that can easily predict human behavior factors. It was seen from their study how the algorithm easily identified significant factors in a sequence of the most affecting to the least significant variable. Several human behavioral studies have also considered either the SEM-neural network integration (Yuduang et al., 2022) or neural networks with other algorithms (German et al., 2022; Ong, 2022, 2022b) which provided viable analysis for human behavior.

With the devastation brought by the typhoons in the Philippines, such as Typhoon Odette, this study evaluated the factors affecting the intention to donate to the victims. This was considered since the event brought attention to other countries, not only limited to Asia. The wide range of donations obtained from other nations have been significant in the Philippines, thus making it the focus of this study. This research considered deep learning neural network (DLNN) which established a classification model to determine the contributing factors affecting the intention to donate for Typhoon Odette victims. This is the first study to assess the intention to donate to natural disaster victims using DLNN. The classification and results may be extended among other natural disaster-related studies focusing on human behavior. In addition, results revealed that the application of DLNN may be considered as a tool for sole or hybrid analyses to evaluate factors affecting human behavior. The findings and framework may be considered by researchers and philanthropists to promote strategies and engage donors for victims of natural disasters and other calamities worldwide.

The flow of the study is presented as (1) Introduction – explaining the background, impact, related studies, research gap, objectives, and significance of the study, (2) conceptual framework which provides the latent variable and hypotheses building, (3) methodology – explaining the data collection process, items of constructs, data processing, and optimization technique, (4) results – which shows the analysis and validity, followed by the (5) discussion, and the (6) conclusion.

2. Conceptual framework

In evaluating health-related risk and behavioral factors, two theories such as the Protection Motivation Theory (PMT) and the Theory of Planned Behavior (TPB) have been widely utilized. It was explained by several studies (Kurata et al., 2022; Ong et al., 2021; Prasetyo et al., 2020) how the integration of both PMT and TPB can holistically measure factors affecting natural disaster-related behaviors. Presented in Fig. 2 is the conceptual framework utilized in this study, integrating both framework for assessment.

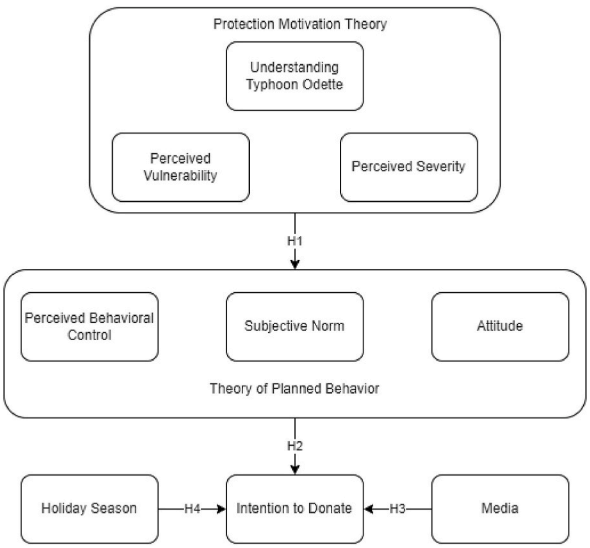

Fig. 2. Conceptual framework.

PMT is a framework utilized to measure threat and coping appraisals with the effect of understanding, knowledge, or experience (Gumasing et al., 2022). Weyrich et al. (2019) explored several factors under PMT and deduced that individuals are more motivated for protective behaviors depending on the protective factors they choose. Studies of Burningham et al. (2007) and Shi et al. (2015) stated that an individual's awareness and understanding of hazards from natural disasters contribute to the communication of risks and effective techniques for disseminating information. In addition, De Coninck et al. (2020) instigated that awareness and perception of both severity and vulnerability expands a person's understanding and knowledge in mitigating the occurrence of danger. It was also presented in the study of Ong et al. (2021) that the perceived severity and perceived vulnerability of an individual greatly affect their intention to perform an act, especially to reduce the impact of natural disaster aftermath. Kling et al. (2021) explained how finance through climate vulnerability affected the cost of equity. It was also explained that economic loss has empirically impacted countries due to the effects of natural disasters, especially in developing countries. The help through donations may mitigate economic losses. Moreover, help through donation contributes to positive and well-established development among responsiveness of the government (Cook et al., 2017). Therefore, it could be posited that factors under PMT contribute and affect the intention among individuals (Gumasing et al., 2022; Kurata et al., 2022). Thus, it was hypothesized that:

Hypothesis 1. PMT factors significantly affect the intention to donate.

TPB is a framework that measures the different behavioral aspects of an individual (Cahigas et al., 2022). Under this theory, perceived behavioral control, attitude, and subjective norm have been stated to holistically measure an individual's intention to perform an act. Aboelmaged (2021) explained how attitude under TPB is one of the antecedents of intention to perform a certain behavior. Hoffmann and Muttarak (2017) and Budhatoki et al. (2020) have presented how the attitude of an individual directly affects their intention to perform an act. The negative attitude will lead to an unwilling intention to prepare. On the other hand, control over one's behavior is positive when people important to them also influence them to perform an act (Ataei et al., 2021). It was indicated by Lin et al. (2020) presented how environmental impacts significantly affect a person's intention. If a person sees the negative implication concerning health, more willingness to help will be seen (Yuduang et al., 2022b). When health is considered, Chuenyindee et al. (2022) indicated that people would have more intentions to help mitigate the aftermath. In this sense, there will be willingness or intention to donate to people who are highly impacted by the aftermath of natural disasters. Thus, it was hypothesized that:

Hypothesis 2. TPB factors significantly affect the intention to donate.

Stewart (2015) explained that sources of information available would help in threat and coping appraisal through emotional aspects brought by the aftermath and consequences of natural disasters. The study of Onyeji-Nwogu et al. (2020) presented how the adoption of people to technology has led to beneficial information and communication abilities. Kirschenbaum et al. (2017) suggested how media affects the positive attitude of an individual which led to a positive effect on different behavioral aspects, such as intention. It was also presented by Becker et al. (2017) how the different forms of media lead to indirect experiences towards social communication in terms of preparedness for hazards such as that of natural disasters. Ong et al. (2021) highlighted the highly significant indirect effect of media as a source of information regarding an individual's intention. Moreover, Guo et al. (2020) showed how the different media platforms are highly considered and utilized for appropriate preparation and information regarding natural disaster events (Kurata et al., 2022), specifically in terms of disasters and crises. Thus, it was hypothesized that:

Hypothesis 3. Media significantly affects the intention to donate.

Since the specific typhoon considered in this study happened during the holiday season of 2021, this study considered the holiday season as a latent variable that may affect their intention to donate to victims. The Christmas season when the disaster struck presented contrast of the common emotions among citizens. In the Philippines, people are usually joyous, presents repentance, calm, lighthearted, has buying and spending sprees, and have grown accustomed to long celebrations – usually four months long (Carbayas and del Castillo, 2020). However, the evident disaster that affected a lot of communities showed that others were willing to help due to the essence of giving and sharing during this season. The study by Pappas (2021) presented the extent an individual will go to experience and feel the essence brought by the holiday season, especially during the COVID-19 pandemic. Hall and Holdsworth (2014) presented the influence of the people affecting the individual during the holiday season. It could be deduced that people have control over their actions during the holiday season to feel it despite the lockdown during the COVID-19 pandemic. In addition, Kasser and Sheldon (2002) presented that increase in happiness among people happens when they spend and give gifts. For these types of events, a donation is one way to give gifts and help others which increases a person's emotional being. Lastly, the study by Jeuring (2017) highlighted the attitude that people feel are being prioritized during the holiday season. Thus, it was hypothesized that:

Hypothesis 4. Holiday Season affects the intention to donate.

3. Methodology

Provided in Fig. 3 is the methodological flowchart of the study. Data was collected through an online survey using an adapted questionnaire. Data pre-processing and data cleaning process was conducted to provide a significant dataset. The cleaned dataset underwent data normalization and parameter setting for DLNN. Validation and verification of the results were examined and interpretation of results followed. The discussion was built on the findings of the study, explained in the latter part of the study.

3.1. Participants

A total of 1077 valid responses were collected through a cross-sectional online survey utilizing Google Forms. The data was

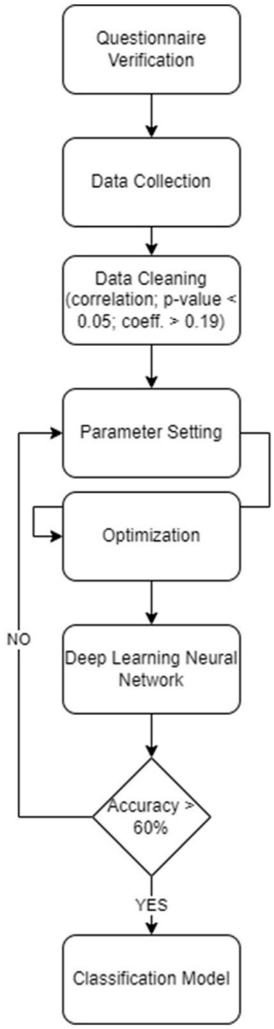

Fig. 3. Methodological flowchart.

collected from December 2021–February 2022 through convenience sampling. Those who are willing or have the intention to donate were asked before they can proceed with the survey. Before data collection, the respondents were asked to consider a confidentiality form ensuring their privacy and information to be kept confidential. In addition, this study was approved by the Mapua University Research Ethics Committees (Document No: FM-RC-21-94). From the collected data (see Table 1), 49% were male and 51% were female with a majority of age ranging from 25 to 35 years old (52.46%) and 36–45 years old (25.53%). Almost all respondents were college graduates (90.16%) with income ranging from 30,001–45,000 PhP (42.97%) or 45,001–60,000 PhP (47.73%) and 93% living in the National Capital Region (NCR), while others are located elsewhere in the Philippines. Before implementing the algorithm, a test for normality was conducted utilizing the Shapiro-Wilks test. The results showed a value within ±1.96 which indicated a normal dataset. In addition, a common method bias (CMB) test was performed using Harman's Single Factor test following the 50% threshold of German et al. (2022). It was seen from the results that the data collected had a 34.02% total variance which indicated no CMB.

3.2. Questionnaire

The items and constructs utilized in this study was adapted from the study of Kurata et al. (2022c). A total of 51 items were considered. The factors under PMT have a total of 18 indicators in total with 6 under Understanding (U), Perceived Vulnerability (PV), and Perceived Severity (PS). TPB indicators have 16 with 6 for Perceived Behavioral Control (PBC) and 5 each for Attitude (A), and Subjective Norm (SN). Lastly, the extensions, Holiday Season (HS) has 6 while Media (M) has 5 to measure Intention to Donate for victims of Typhoon Odette (I). A total of 54,927 datasets were considered.

Table 1
The demographic of the respondents (n = 1077).

Characteristics	Category	n	%
Gender	Male	528	49.00
	Female	549	51.00
	20–24 years old	91	8.450
	25–35 years old	565	52.46
Age	36–45 years old	275	25.53
	46–60 years old	139	12.91
	More than 60 years old	7	0.650
	College Students	49	4.550
Education Status	Vocational Graduate	1	0.090
	College Graduate	971	90.16
	Master's Degree Graduate	54	5.010
	PhD Graduate	2	0.190
Monthly Income/Allowance	15,001–30,000 PHP	82	7.610
	30,001–45,000 PHP	452	42.97
	45,001–60,000 PHP	514	47.73
	60,001–75,000 PHP	14	1.300
	More than 75,000 PHP	15	1.390
	CAR	8	0.740
	NCR	1002	93.05
	Region I	2	0.190
	Region II	4	0.380
	Region III	22	2.040
	Region IV-A	27	2.510
	Region IV-B	1	0.090
Location	Region V	4	0.371
	Region VI	3	0.279
	Region VII	0	0.000
	Region VIII	1	0.090
	Region IX	1	0.090
	Region X	1	0.090
	Region XI	0	0.000
	Region XIII	0	0.000
	BARMM	1	0.090

3.3. Data pre-processing

The 54,927 datasets underwent data pre-processing for consideration of the Deep Learning Neural Network (DLNN). For the data pre-processing, the collected data were first inspected for missing values or outliers. After this, Harman's Single Factor Test for Common Method Bias was analyzed which produced a value of 43.12% which is less than the threshold set by Podsakoff et al. (2003). This indicates that the collected data may be utilized.

For the data cleaning process, the dataset was run utilizing correlation analysis. A threshold of 95% confidence interval for the p-values and 0.20 correlation coefficient were considered significant (Ong et al., 2022b, 2022c; Yuduang et al., 2022). After the data cleaning, data aggregation of the remaining indicators considered mean values to represent the different latent variables considered as input nodes for the DLNN. Lastly, the min_max scalar for data normalization was considered. Lastly, parameter setting was considered to obtain the optimum DLNN model.

The DLNN as explained in the study of Ong et al. (2022b) is a classification model that considers two or more hidden layers to calculate the output node representing the dependent variable, Intention to Donate for victims of Typhoon Odette (I). Based on related studies presented, DLNN would be applicable if the simple ANN classification algorithm cannot produce a higher accuracy rate which results in lesser computational complexity in analyzing patterns in a dataset. The presence of more hidden nodes in the model would provide higher calculation complexity for the analysis. Thus, this study considered DLNN since the initial attempt to use ANN results to lower the overall accuracy rate. The input nodes considered in this study were Understanding of Typhoon Odette (U), Perceived Vulnerability (PV), Perceived Severity (PS), Perceived Behavioral Control (PBC), Attitude (A), Subjective Norm (SN), Holiday Season (HS), and Media (M). It was explained that DLNN would be highly considered especially with complex nonlinear relationships present in the framework (Aggarwal, 2019). Since this study considered a large number of datasets, and complex framework interrelationships, and aimed to determine factors affecting human behavior, DLNN has been said to be one of the best predictive tools to create a classification model for pattern recognition (Aggarwal, 2019; Caldwell et al., 2021; Ning et al., 2020).

3.4. Deep learning neural network optimization

A total of 21,600 runs were considered for the initial optimization process. The hidden layer considered several activation functions such as Elu, Swish, and Tanh. Moreover, the number of hidden layers was also considered. Determination of nodes from the first hidden layer with intervals of 10 until 100 with 15 nodes in the second hidden layer was set. The output layer considered activation functions of Relu, Softmax, and Sigmoid. The optimizer of SGD, Adam, and RMSProp was considered. These parameters were considered based from adopted activation function of related studies that utilized neural networks in the context of natural disasters as presented in Table 2.

In addition, the optimization process considered 10 runs per combination with an epoch set at 150 (Pradhan and Lee, 2010; Satwik and Sundram, 2021). At 80:20 training and testing ratio, the process considered Python 5.1 upon running the DLNN. It was seen from the initial optimization that Tanh for the hidden layer activation function, Softmax for the output layer, and Adam as the optimizer presented the highest accuracy. Thus, these parameters were further utilized for the final DLNN optimization to obtain the optimum DLNN model. The pseudocode is presented as follows:

Step 1. Preprocessed data loading

Step 2. Normalization using min_max scalar

Step 3. Feature selection of variables and setting

Step 4. Train_test_split package for training:testing with zero random states using sklearn.model_selection

Step 5. Keras sequential from Tensorflow for parameters and number of nodes in layers of DLNN

Step 6. Parameter setting of hidden and output layer activation functions

Step 7. Optimization of the number of hidden layers and number of nodes

Step 8. Setting optimizers for the optimization process

Step 9. Calculation of feedforward process setting parameters of weights (w), bias (b), learning rate, and epochs for iteration

#DLNN Calculation using:

$$s_j = \sum_{i=1}^{n} w_{ji}\, x_i + b_j = W_j\, X + b_j$$

And the output (y) calculated with their activation function (S_j) as:

$$y_i = f(S_j) = f\ \sum_{i=0}^{n} w_{ji} x_i = F(w_j X)$$

Step 10. Print(validation), Print (accuracy), Print (precision), Print (recall values), Print (loss rate)

4. Results

With the utilization of Tanh for the hidden layer activation function and Softmax for the output layer, an 80:20 training and testing ratio was utilized with Adam as the optimizer using 200 epochs to further run the DLNN. It was indicated from the study of Ong et al. (2022b; 2022c) that the average testing result would lead to the ranking of the significant latent variable. In addition, Asadikia et al. (2021) explained how only those resulting with accuracies greater than 60% will be considered significant.

Tanh was seen to be the best activation function for the hidden layers in the DLNN similar to other studies (Gudivada and Rao, 2018). It added how the Tanh activation function is best for calculating nonlinear relationships. Tanh is great for calculating these types of models, especially when the parameters such as the nodes are optimized (Walrave et al., 2021). Equation (1) represents the Tanh activation function:

$$\tanh(x) = \frac{2}{1+e^{-2x}} - 1 \tag{1}$$

Table 2
DLNN parameters.

Parameters	References
Hidden Layer Activation Function	
Swish	Sharma et al. (2020)
Elu	Feng and Lu (2019); Eckle and Schmidt-Hieber (2019)
Tanh	Sharma et al. (2020); Feng and Lu (2019); Eckle and Schmidt-Hieber (2019)
Output Layer Activation Function	
SoftMax	Pi et al. (2020); Anbarasan et al. (2010); Satwik and Sundram (2021), Sharma et al. (2020)
Relu	Jena et al. (2020); Jena and Pradhan (2020); Yousefzadeh et al. (2021)
Sigmoid	Elfwing et al., 2018
Optimizer	
Adam	Eckle and Schmidt-Hieber (2019)
RMSProp	Yousefzadeh et al. (2021)
SGD	Jena et al. (2020); Jena and Pradhan (2020)

On the other hand, the output layer considered Softmax as the best activation function as represented in equation (2). Softmax is considered one of the parameters with advantageous output since it considers all output and compares the result individually. This is best to use, similar to Sigmoid since the calculation after the hidden layers has established smaller values which presents a more efficient calculation (Liébana-Cabanillas et al., 2017).

$$softmax\left(z_j\right) = \frac{e^z j}{\sum_{k=1}^{K} e^z k} \tag{2}$$

Lastly, Adam as the optimizer considers the minimization of losses when processing the neural network (Kingma and Ba, 2015). It was stated by Kalinić et al. (2021) how optimizers such as Adam influences the training result which presents a great output, to which this is usually utilized. Kingma and Ba (2015) highlighted the efficient output when Adam is utilized due to little memory usage but can consider large datasets. Represented in equation (3) is Adam when utilized as an optimizer.

$$w_t = w_{t-1} - n\frac{m_t}{\sqrt{v_t} + \in} \tag{3}$$

Table 3 shows the summary of DLNN results. It is seen how Perceived Severity (PS) and Perceived Vulnerability (PV) have the highest significant effect on the intention to donate to Typhoon Odette victims. Following this is Understanding of Typhoon Odette (U), Subjective Norm (SN), Media (M), Perceived Behavioral Control (PBC), Holiday Season (HS), and Attitude (A) which all generated accuracies greater than 60%. This indicates highly significant factors (Asadikia et al., 2021; Ong et al., 2022b, 2022c).

Similarly, a test of importance was considered to further validate the findings of this study. Presented in Table 4 are the score and normalized score of importance which coincides with the DLNN results. Therefore, it could be deduced that the most significant factors are PS and PV with A as the least, but still highly significant factor.

No overfitting is seen from the optimization run utilizing the 200 epochs at an 80:20 training and testing ratio as presented in Fig. 4. Thus, the generation of the optimum deep learning neural network model was conducted. The optimum model is presented in Fig. 5 with the different factors as the input nodes, 40 nodes for the first hidden layer, 15 nodes for the second hidden layer, and intention as the node representing the output layer. An overall 97.12% accuracy of the model is seen at the optimum parameters. In this case, the validation loss rate is closely in line with the training loss rate which indicates no over (under)fitting. The greater the distance of the validation to the training loss rate, an overfitting outlook will be seen. On the other hand, if the validation loss rate will be way below the training loss – an underfitting – means that the accuracy rate is low will be seen (Yuduang et al., 2022).

For the validation of the model, a Taylor Diagram was conducted for the acceptability of the classification model. As seen in Fig. 6, the relationship through the curvature of correlation, standard deviation, and root mean square error (RMSEA) has been presented. Following the suggestion of German et al. (2022), a 90% correlation value would be considered significant with a RMSEA of 20%. The standard deviation as indicated in the Taylor Diagram was set and shown as the *star* legend. The result showed consistent findings with high correlation; thus, accuracy rates were seen to be significant and posit an acceptable classification model from DLNN.

5. Discussion

The constant threat and devastation from natural disaster aftermath across the world have brought negative effects on livelihood, infrastructures, economy, and even lives. The platforms available for donation have significantly helped overcome these problems. However, the need to promote and reach different people may increase the amount collected and thereby easily help others. This study aimed to utilize deep learning neural network (DLNN) to create a classification model to measure the most significant factor affecting the intention to donate (I). These factors are Perceived Severity (PS), Perceived Vulnerability (PV), Understanding of Typhoon Odette (U), Subjective Norm (SN), Media (M), Perceived Behavioral Control (PBC), Holiday Season (HS), and Attitude (A).

From the DLNN results, PS showed the highest accuracy with a 100% score of importance. It was seen that donors know how severely affected the country is by the typhoon; the frequency of different typhoons as well as the effect of the typhoon on the country were also indicators. It could therefore be deduced that people's perception of how they accept the situation affects predisposition. Salo et al. (2013) support this claim and explained that this predisposition affects the way they act on a subject matter. With available resources, Armitage and Conner (2001) stated that people would be willing to act. Burningham et al. (2007) and Shi et al. (2015) confirm the relationship between PS and I and state that the communication between individuals due to the perception of severity and vulnerability leads to a more influential communication among individuals. The hazard brought by natural disasters contributes to an

Table 3
Summary of DLNN results.

Latent	Average Training	StDev	Average Testing	StDev
PS	85.42	3.361	94.59	3.520
PV	85.61	2.363	94.20	4.292
U	85.05	4.927	93.62	4.034
SN	87.44	5.107	92.49	5.095
M	85.51	5.000	91.39	3.217
PBC	85.15	3.424	87.18	3.771
HS	83.38	2.035	84.77	2.692
A	82.71	2.810	80.11	3.348

Table 4
Score of importance.

Latent	Importance	Score (%)
PS	0.238	100
PV	0.234	98.35
U	0.231	97.16
SN	0.227	95.24
M	0.222	93.34
PBC	0.216	90.86
HS	0.204	85.72
A	0.198	83.28

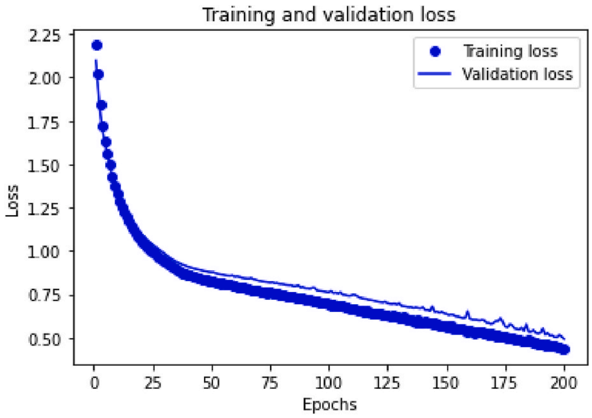

Fig. 4. Training and validation loss rate.

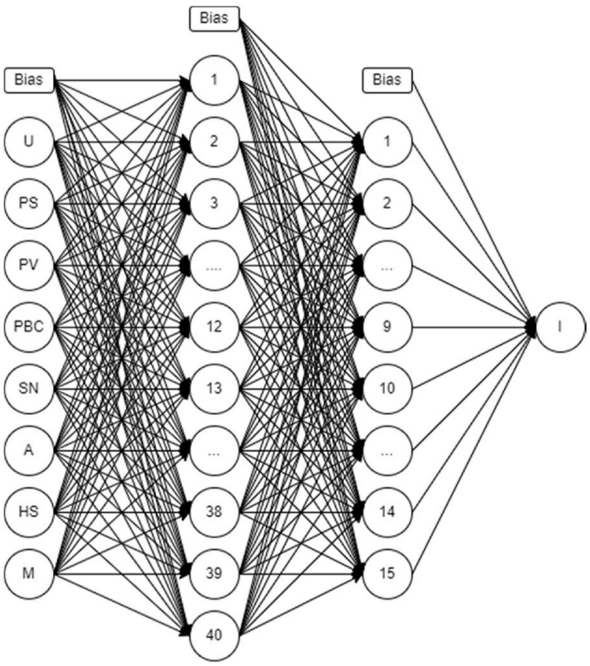

Fig. 5. Optimum deep learning neural network model.

effective technique for information dissemination. Lastly, De Coninck et al. (2020) presented how perception and awareness of both severity and vulnerability affect an individual's mitigation and intention due to the foreseen danger.

PS was seen to have the second highest significant effect with 98.35%. The past experiences, destruction of infrastructure,

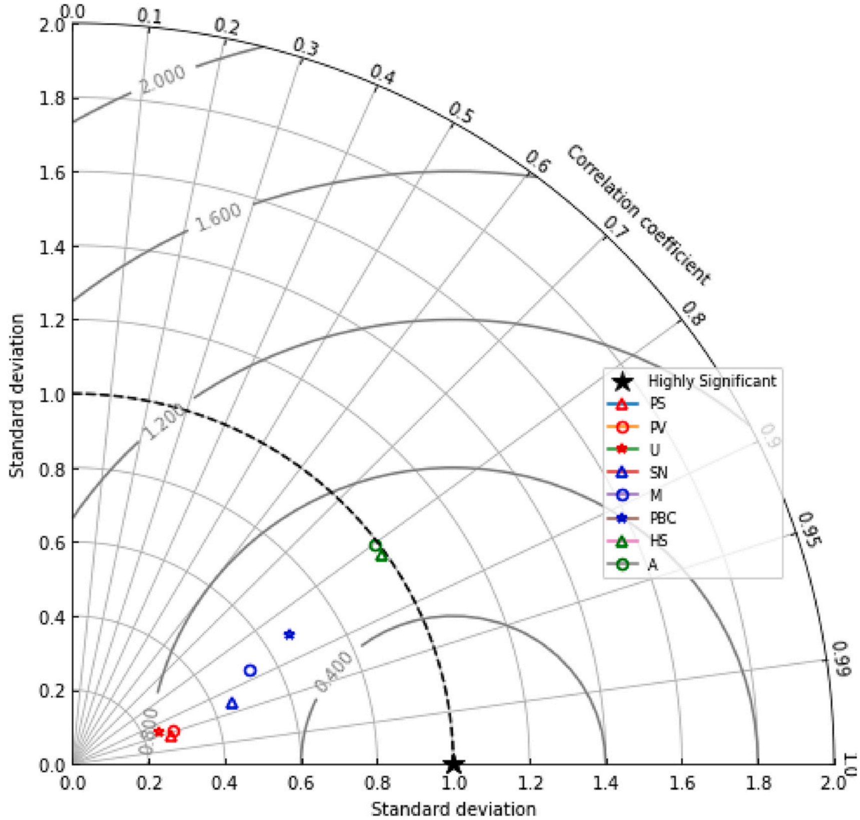

Fig. 6. Taylor diagram.

livelihood, and negative effects of typhoons were seen to be indicators that affected donors' intention to donate to Typhoon Odette victims. However, studies such as that of Deng et al. (2020) presented that PS will only be considered significant if there is danger or whether the individual is in a life-threatening scenario. They indicated that the factor may be insignificant if the threat is low or may not be available. In accordance, the results imply that an impactful natural disaster would always lead to PS being significant since it is inevitable when its aftermath and impact are great.

U was seen to be a highly significant factor (97.16%) affecting I. The indicators that preceded U were the notion that donors understood the impact, danger, and overblown affected areas. A positive and highly significant relationship was seen which is similar to the findings of Becker et al. (2017). Ong et al. (2021) also presented how U is an antecedent of both PS and PV that affects a person's intention. The presence of available information on natural disaster nowadays have helped donors with which areas are affected, how greatly the people are affected, and its effect on the economy and livelihood (Guo et al., 2020). This led to the donor's proper information and understanding of natural disasters such as the Typhoon Odette that affects their intention. The availability of mass media has therefore influenced not only in understanding and information but has also promoted platforms for donors to give help. To which, M played a significant role (93.34%) towards the donors' I. The more people understand the effects of natural disasters, the more they are likely to help and act upon the situation, especially when death and destruction are prevalent (Liu et al., 2019). On the other hand, Chmutina and von Meding (2019) showed that understanding would be inclined more toward perception rather than one's own state of mind, especially when influenced by others. In this study's case, the impact of media influence an individuals' U to see the impact of typhoon Odette which increased their perception of its aftermath.

SN has a significant effect (95.24%) on I. Ong et al. (2021) and Arafat et al. (2018) explained that the more favorable the behavior is, the more likely an individual would act in response to it. This explains that positive behavior would be followed by an individual. In this case, when people are in need and individuals see how other people would help, then it would be more likely that people would help. The indicators presented how people have the feeling that they are obliged or pressured to donate due to the influence of people around them, people who are around the individual expect a pledge from the donor, and if people around them donate, people would do the same. These findings are also similar to the effect of positive behavior influenced by other people around them (Manning, 2009). This supports how PBC was seen to have a significant role (90.86%) towards I. The influence and control over the donors' behavior were evident. It can also be deduced that people expect and know what the outcome after a massive typhoon is, they know how to search for information and available platforms for help, and that any help may or may not be given will be up to them. These indicators represent the donors' control on their intention to help via donations for Typhoon Odette victims. However, Ong et al. (2021) highlighted that if people around an individual do not present relatable factors, then, people would not have a high significance of SN.

In this case, victims were centered and donors highly empathize among individuals which is why SN was seen to have a high significance rate.

Moreover, HS was a significant factor affecting I, showing an 85.72% score of importance. Super Typhoon Odette happened in late December of 2021 which is the Christmas season. The indicators presented how donors are likely to donate due to the holiday season – the time for giving is present and donors are accustomed to it, feel more compassionate, want to be influential in donating, and be a blessing to others. Pappas (2021) showed how the holiday season is prominent among individuals despite the presence of the COVID-19 pandemic since they have control over their behavior. In addition, Hall and Holdsworth (2014) and Jeuring (2017) presented how individuals have the capabilities to feel comfortable and to embody a positive attitude during the holiday season. As reflected in this study, donors intend to donate to Typhoon Odette victims as seen from the indicators. The studies presented showed highly significant HS as a latent variable. On the contrary, most HS latent variables are measured during vacation behavior or fun activities. Thus, in contrast to the findings, helping others in need highlights sympathy rather than the influence of the season.

Lastly, A presented to be a significant factor affecting I with an 83.28% score of importance. Despite being the last factor affecting donors' intention, the A factor is still highly significant with the importance score and accuracy presented (80.11%). People understand and find it difficult to cope with the typhoon aftermath, have the feeling of worry and stress, and empathize for the victims of the natural disaster. In line with the findings, Liu et al. (2019) showed how a positive attitude would lead to help and reduce the number of casualties. In addition, Ong et al. (2021) highlighted a strong relationship between A and intention. Similarly, Chou et al. (2015) explained that A is an influential factor in the behavior of an individual. Lastly, Paul and Bhuiyan (2010) showed how A influences an individual's intention and preparedness of individuals.

Overall, it could be seen that donors have control and will look for ways to help and donate, seek information, support the donation, and help casualties of Typhoon Odette victims. The perceived severity and perceived vulnerability lead to more understanding and compassion to the victims of the typhoon. In addition, the understanding of donors led to a more positive intention aside from the damages seen due to the location. Thus, it could be deduced that donors are more likely to donate if the damages, severity, vulnerability, and aftermath are destructive due to the natural disaster.

5.1. Theoretical and practical implication

The available data nowadays are considered to be highly valuable. Frey and Rusch (2014) utilized neural networks to recognize patterns and indicated their robustness and high predictive power. Similarly, pattern recognition was seen with the use of deep learning neural network in this study. Onyeji-Nwogu et al. (2020) and Kaliba et al. (2020) presented that the information obtained from machine learning algorithms such as deep learning neural network performs better with higher accuracy of prediction. From the results of this study, it could be deduced that behavioral patterns are seen based on the significant factor affecting the intention to donate to victims of Typhoon Odette.

Practically, if the perceived severity, perceived vulnerability, and understanding of the natural disaster and its aftermath are presented, people will have high intentions to donate. Highly significant factors of influence by other people, media, and attitude would also influence the control over an individual's donation intentions. It could therefore be highlighted by platforms how super typhoons would affect infrastructures, lives, and livelihood of people in a community. An example would be presenting the devastation of the natural calamity and its aftermath among different regions severely hit. In this way, the perception of vulnerability and perceived severity may be highlighted. In addition, the severity and vulnerability may also be considered and presented to encourage more engagement of donations. In the case of Understanding, platforms may want to highlight information regarding natural disasters to provide a platform for related events that donors may need. The platforms for donation as media may consider the findings of this study to create more influential broadcasts regarding the need for donation among victims of natural disasters through the use of different media available.

5.2. Limitations

Despite the relevant and significant findings presented in this study, several limitations could be posited the present study. First, due to the lockdown brought on by the COVID-19 pandemic, the collection of data was only done through a collection of responses with an online questionnaire. It is advised to create interviews and group discussions for the collection of more information. Future researchers may also obtain relevant information and extend frameworks through factors that could be discovered from the interviews. Second, this study considered only one machine learning algorithm. Despite being one of the most sophisticated tools, DLNN may be supported by other machine learning algorithms like Naïve Bayes that consider probability-type of calculation and analysis. Lastly, clustering of donors may also be done to segregate and group the different types of donors and highlight the different indicators that would lead to a more concise separation of factors affecting the intention to donate to natural disaster victims.

6. Conclusion

World development is needed especially with the economic loss brought about by the COVID-19 pandemic. Given that, natural disasters affect infrastructures, the agricultural sector, livelihood, and lives in general, the difficulty of this development is highly evident. This study aimed to analyze factors influencing the intention to donate for the victims of typhoons utilizing a deep learning neural network. The need to assess the influential factors would be beneficial to help the economy rise after the natural disaster aftermath and promote world development.

The findings presented how perceived severity, perceived vulnerability, and understanding of the natural disaster highly affected the intention of donors to give to victims of Typhoon Odette. It was seen that when people know the effect of disastrous events, and vulnerability due to location, and information on the situation, more likely they would donate and help the victims. In addition, people around the individual, empathy, a positive attitude, and the holiday season influenced the feeling of giving and donors were seen to have control over their behavior. It could then be posited that the impact of a natural disaster influences other people as well as donors which will lead to a positive effect on their intentions to donate to victims of natural disasters. Since the results were validated and showed high calculation complexity and accuracy when analyzing the nonlinear relationships, it could be deduced that MLA such as DLNN can be applied in human behavior studies. The method, framework, and findings of this study may be considered and applied to other researches focusing on natural disasters. In addition, the government and donation platforms may capitalize on the findings of this study to communicate and promote engagement for donations from people in different countries. The application of results may also be applied and extended for other research regarding intention, natural disasters, and behavioral studies worldwide.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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