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Which Factors Can Contribute to the Success of Environmental and Animal Protection Projects in Donation-based Crowdfunding? A Neural Network Model

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Abstract
The crowdfunding industry has developed rapidly in recent years, the existing research shows that crowdfunding can help in many fields such as entrepreneurship, creative products, or donations. Due to global meteorological issues, more and more people are paying attention to the environment and animal protection. However, fundraising in these areas has been the biggest problem, the emergence of donation crowdfunding (DCF) can alleviate this dilemma. Currently, in academia, there is still less research focused on crowdfunding for environmental and animal protection. This paper aims to study the factors influencing the successful financing of environmental and animal protection projects in the DCF. This paper analyses 700 DCF environmental and animal protection projects in China as samples, and creatively introduces financial transparency scoring indicators. Through binary logistic regression, financial transparency was found to be the most critical positive factor affecting project success. At the same time, donors receive NPO-initiated projects well, and the number of donors can also positively impact the results. However, the excessive description of the projects can have the opposite effect. This study also introduced a neural network model, and found that the neural network model can optimize the discriminant accuracy of the traditional binary logistic regression model.

Keywords: Crowdfunding, Donation Crowdfunding, Environmental and Animal Protection, Financial Transparency, Neural Network.

1. INTRODUCTION

In recent years, the rise of the Internet has propelled the development and revolution of donation (Li et al. 2020). In China, more than US$1,290.66 million was raised from 20 Chinese Internet fundraising platforms for charities in 2020. Further, a year-on-year increase of 52%, and more than 10 billion people participated in online donations (*2020 China Charitable Donation Report*, 2020).

Crowdfunding is a method of financing developed based on the prosperity of the Internet. The main idea of crowdfunding is that people who need funds present their projects through online crowdfunding platforms and connect with people willing to support them. It involves multiple actors, such as individuals, entrepreneurs, NGOs, and project backers. According to existing research, there are four recognized types of crowdfunding: equity crowdfunding, reward crowdfunding, lending crowdfunding, and DCF (De Buysere et al., 2012; Jiang et al., 2021). Equity crowdfunding refers to project backers obtaining shares or similar rights of the project sponsor by supporting crowdfunding projects. Reward crowdfunding means that project backers can receive non-monetary rewards for supporting the project, such as limited edition signed CDs or priority access to new products. Lending crowdfunding refers that project sponsors obtaining a lower cost of capital, and lenders will also have high-return investment opportunities. DCF is a crowdfunding model that raises funds from the public through crowdfunding platforms to help those in need (Belleflamme et al., 2014). Non-profit projects in crowdfunding can often raise funds more quickly than other projects due to social capital (Buttice et al., 2017). Due to ethical reasons, non-profit projects are more likely to be trusted by the general public. DCF projects are typical non-profit projects. What is special about this type of crowdfunding project is that the project backers of the other three usually get some return, whether monetary or non-monetary, in DCF this is uncommon. Whether it is protecting the ecological environment or saving a homeless stray cat, providing medical assistance to those in need, or helping the disadvantaged in society, DCF seems to be an invisible hero who has become a lifesaver. DCF has revolutionized the traditional donation model, but its goal remains to help those in need to access funds (Özdemir et al., 2015).

Existing research on DCF mainly focuses on donor motivation and project sponsors. Few studies have considered transparency in discussing projects from a financial perspective. The most crucial factor affecting general donation behavior is transparency, and the online DCF has its particularity, making its projects more difficult to control. Some studies have begun to focus on this online-offline gap, such as Salido-Andres et al. (2021).

Environmental and animal protection have received global attention in recent years. Most NGOs currently rely heavily on donations, which are also an important funding source for environmental and animal protection work (Veríssimo et al., 2018). The major problem faced by this type of project is the shortage of funds(Waldron et al., 2017). DCF can help alleviate the current massive funding gap. Currently, most research on environment and animal protection focuses on offline fundraising projects, and there is little research on online donation projects (Veríssimo et al., 2018; Lundberg et al., 2019). Gallo-Cajiao et al. (2018) have paid attention to DCF projects focusing on environmental protection and studied the factors that influence its success. Also, some studies have confirmed that marketing tactics are more influential than hot topics on the success of environmental donation projects (Kubo et al., 2021). The practical significance of the present research is how to help environmental and animal protection practitioners obtain more support.

In addition, it has to be mentioned that with the rapid development of big data in recent years, artificial intelligence has been used in various industries. However, most current research on crowdfunding is still exploring traditional regression models. Machine learning can already challenge human experts in multiple fields (LeCun et al., 2015). In the field of social sciences, many studies have begun to use artificial intelligence (AI) tools to analyze data more efficiently (Mullainathan & Spiess, 2017). As the most representative part of AI, many studies have long used neural network models to better process sample data. Therefore, this research will establish a Backpropagation (BP) neural network model based on the traditional multiple linear regression model, study the influencing factors of the success of DCF projects for environmental and animal protection, and compare the ability of the two models to predict project success.

2. LITERATURE REVIEW

2.1 Donations and DCF

Traditional donations and DCF share a great degree of similarity. Given the narrow focus of existing research on DCF, this study will briefly review the existing literature on DCF and traditional donations. In addition to Gallo-Cajiao et al. (2018) and Kubo et al. (2021) who mentioned above have focused on environmental and animal protection, this paper finds that most of the existing research on DCF is usually divided into two aspects: the research on the donor and the project sponsor. For donors, it typically orbits around donation motivation, as shown in Table 1.

ID	The main point of view	Authors
1	Emotion-based	Isa et al. (2015); Body & Breeze (2016); Moritz & Block (2016)
2	Altruism or sacrificialism	Gleasure & Feller (2016); Liu & Hao (2017); Majumdar & Bose (2017); Y.-Z. Li et al. (2018)
3	A sense of belonging	Smith et al. (2015); Cockrell et al. (2016); Lacan & Desmet (2017); Neumayr & Handy (2019);
4	Other	Verhaert & Van den Poel (2011); Althoff & Leskovec (2015)

Table 1. Research on donation motivation

Some studies have proposed emotion-based donation motives, such as Isa et al. (2015) took into account that a person's self-perception can influence donation behavior. Body & Breeze (2016) believed that one of the essential donation motivations is emotion, which can increase the willingness of donors by describing the cause or increasing the donation amount. Moritz & Block (2016) also have similar views. They believed donors' giving behaviors are realized through the intrinsic motivation of personal interests, beliefs, empathy, social influence and trust, and the extrinsic motivation to improve social problems and knowledge.

Some studies suggested that this is a form of altruism or sacrificialism. Gleasure & Feller (2016) found that donors of DCF projects are motivated by pure altruism. Liu & Hao (2017) thought of donations as an act of sacrifice, and interestingly, donors often look forward to possible future returns that are generally not financially derived. Similarly, Majumdar & Bose (2017) argued that donors in DCF help people in need based on emotional rather than financial rewards. On this basis, some studies have also found that performance expectancy and effort expectancy are essential factors in determining donation behavior. These backers know they won't get a monetary return and are willing to back projects they love, a motivation different from those of other types of crowdfunding (Li et al., 2018).

The reason for motivation may also stem from a sense of belonging. Lacan & Desmet (2017) found that the cause of individual donors is a sense of belonging to the community. Because of prosocial emotional and empathic concerns, individual donors' emotional skills and abilities also motivate them to donate (Neumayr & Handy, 2019). Differently, age may also be an essential factor in donation motivation. Cockrell et al. (2016) believed that DCF donors are affected by age, with younger donors more inclined to donate to DCF projects. Interestingly, Smith et al. (2015) considered the "peer effects" of the donor to be significant in the donation process. By studying donor responses to "peers" who donated simultaneously, they found that donor behavior was influenced by early donation information so past donations can also affect future donation motivations.

In addition, some studies have focused on other donation motivations. Verhaert & Van den Poel (2011) found that traditional donations are generally made by mail. Future donations could be predicted based on the frequency and amount of donors' past contributions. Similarly, Althoff & Leskovec (2015) studied that a proportion of donors continued to donate after the success of their first donation project, the authors also proposed that past projects' success can influence donor motivations.

Some existing literature also studied DCF sponsors, as shown in Table 2. For example, some studies focused on the relationship and interaction between donation sponsors and donors, and their impact on the fundraising capacity of donation projects. Mano (2014) believed that using social media promotes donations for DCF projects. The increase in the online donation rate does not affect the situation of offline donations because social media use affects donors' awareness of social issues, which increases their voluntary participation and contributions to DCF projects. Althoff & Leskovec (2015) explored how the DCF platform influenced donors' giving behavior. Timely and positive interaction and recognition of their donation behavior can improve donor retention rates and prevent donors from losing on the platform. Choy & Schlagwein (2016) found that whether project sponsors use crowdfunding platforms for fundraising or not will not affect the final fundraising results.

ID	The main point of view	Authors
1	The relationship and interaction	Mano (2014); Althoff & Leskovec (2015); Choy & Schlagwein (2016)
2	The fundraising system	Buccoliero et al. (2015); Solomon et al. (2015); Beltran et al. (2015)
3	The distribution of donations	Ndeffo Mbah & Gilligan (2011); Dragojlovic & Lynd (2014); Lee et al. (2016); Tan et al. (2021)

Table 2. Research on the project sponsor

In online fundraising, the fundraising system will also impact the fundraising results. Buccoliero et al. (2015) studied the impact of mobile communication technology on donations, and they found that donation projects through mobile Internet can get more support. Solomon et al. (2015) focused on the impact of DCF project deadlines on donor motivation, and they found that project sponsors can promote project progress if they can attract donations in the early stage. Beltran et al. (2015) studied the impact of conditional donations on DCF projects. By introducing a crowdfunding system CODO (Conditional Donations) and designing the DCF interface, donations will only be made when the project meets certain donation criteria. They found that more donors chose conditional donations than general programs.

Other scholars have paid attention to the distribution of donations, such as the optimal distribution of donations received, which can be confirmed by an agent-based simulation model (Ndeffo Mbah & Gilligan, 2011). Dragojlovic & Lynd (2014) proposed that in some particular fields, such as medical oncology and rare disease drug development, researchers can obtain some initial funding through DCF. It is an essential driver for DCF project sponsors, although it is not a substitute for government funding. Similarly, Lee et al. (2016) also adopted an agent-based simulation model to distribute donations between projects efficiently. It can also be consistent with the donor's preferred project, thereby increasing the success rate of the DCF project. Tan et al. (2021) proposed that, unlike traditional donation methods, through DCF, donors can decide the distribution of donations and choose their preferred projects and beneficiaries. This change will also increase the donation number of donors.

2.2 Artificial Intelligence, Neural Networks and Crowdfunding Successful Prediction

In recent years, artificial intelligence and machine learning have been constantly mentioned by scholars. Machine learning has also become an efficient tool for researchers in data analysis and has been applied to various research fields (Ghahramani, 2015). As one of the essential fields of artificial intelligence, artificial neural network (ANN) has also developed rapidly. Many existing studies have proved the advantages of the ANN model in data regression prediction analysis, and the ANN model has a good performance in optimizing the prediction ability of traditional models (Thakial & Arora, 2019).

Many scholars have confirmed that ANN models can optimize crowdfunding project success predictions, which can help all participants in crowdfunding. Earlier studies, such as Greenberg et al. (2013), pioneered testing a variety of machine learning classifiers, and their model was able to predict crowdfunding project success with 68% accuracy. Mitra & Gilbert (2014) studied a large amount of phrase data from crowdfunding platforms and social media based on neural network models, they found that the data can be surprisingly predictive of the success of crowdfunding projects. Li et al. (2016) defined the success of crowdfunding projects as a matter of survival. They also developed a neural network algorithmic model to predict the success of crowdfunding projects based on big data from Twitter. Similarly, Lee et al. (2018) established an ANN prediction model and proved through empirical research that the ANN model can accurately predict the success of crowdfunding projects.

In DCF's research, there is enormous variability between projects and much uncertainty about donors so that machine learning can capture the nuances correctly. Cheng et al. (2019) developed a multimodal crowdfunding neural network prediction model, which can recognize information such as images, text, phrases, etc., and improve the prediction ability of the machine learning model. Wang et al. (2020) compared standard machine learning algorithm models, including decision tree, random forest, logistic regression, support vector machine, and K-nearest neighbors. After adjustment, their neural network algorithm model can predict crowdfunding results with 92.3% accuracy. Shi et al. (2021) focused on the impact of audio information on crowdfunding project success. They trained an audio perception model through machine learning techniques and used it to predict the success of crowdfunding projects. In addition to audio information, there is also video information. Korzynski et al. (2021) established a machine-learning model based on video information released by crowdfunding projects to predict the success of crowdfunding projects.

In addition to neural networks, some authors, such as Duan et al. (2020), have also focused on the application of machine learning in predicting the success of crowdfunding projects. Based on facial recognition technology, they found that the facial credibility of project sponsors can affect the success of crowdfunding projects. Similarly, Yeh & Chen (2020) built a successful prediction model for crowdfunding projects based on big data from social media, and their research developed a machine learning modeling method to extract relevant features of crowdfunding projects. Peng et al. (2021) developed an integrated machine-learning algorithm model to predict the financing performance of crowdfunding projects. Jiang et al., (2022) used neural networks in the equity crowdfunding success factor analysis model, and their model predicted project success with a 97% accuracy rate.

With the literature analyzed, this study identified the following research questions:

RQ1: What factors will affect the success of environment and animal protection DCF projects in China analyzed through BP neural network models?

3. SAMPLE, VARIABLE AND INSTRUMENT

3.1 Sample

This paper uses the projects on China's largest DCF platform "Tencent Public Welfare" as a sample because it has the most environmental and animal protection projects. This paper selects all environmental and animal protection projects that have completed donations on the platform as samples. After excluding items with incomplete data, 700 items were finally obtained. Considering the particularity of these projects, they are independent, decentralized, and cannot be collected by existing technologies, so this research collected them manually.

3.2 Variables selection

Regarding the selection of variables, this paper selects variables commonly used in existing DCF research. The definitions and sources of the variables are shown in Table 3.

Abbreviation	Variable	Definition Explanation	Source
R	Result	The dependent variable as the "success R" of the project, which is a binary variable. When the actual fundraising amount reaches the target amount, R is "1", indicating that the project is successful. Otherwise, R is "0", indicating that the project fails.	Calculated in this paper
ND	The number of donors	The number of donors is often used in DCF research and is the most intuitive measure of a project's popularity (Belleflamme et al., 2014).	Platform "Tencent Public Welfare"

T	Project sponsor	Usually an individual or NPO, which is a binary variable, which may influence the motivation to donate.	Platform "Tencent Public Welfare"
NW	The number of words	The content of the project presentation may also affect the final donation amount (Solomon et al., 2015; Gallo-Cajiao et al., 2018).	Platform "Tencent Public Welfare"
NP	The number of pictures	The content of the project presentation may also affect the final donation amount (Solomon et al., 2015; Gallo-Cajiao et al., 2018).	Platform "Tencent Public Welfare"
TS	Transparency score	Developed based on four indicators that measure transparency. Each indicator corresponds to one point. Four points are awarded if four indicators are met. The higher the score, the more complete the materials, the clear and transparent the use of raised funds, and the more transparent the information disclosure of project sponsors.	Calculated in this paper

Table 3. Variable definitions

Table 3 shows the definitions, interpretations and sources of all variables in this paper, depending on the goals, this paper hopes to examine what factors influence the success of environmental and animal protection projects in DCF. Then this paper defines the dependent variable as the result "R" of the project. The target completion rate is not considered in this study because the target fundraising amount of the project is different, and the difficulty of achieving the same degree of completion is also different. Hence, it is not meaningful in this paper.

In addition, this research considers project financial transparency as a variable (Zainon et al., 2014; Král & Cuskelly, 2018; Ortega-Rodríguez et al., 2020). In measuring transparency, this paper collects four variables, shown in Table 4.

ID	Variable	Source
a	Whether there is an invoice	Platform "Tencent Public Welfare"
b	Whether the invoice is complete	
c	Whether there are financial statements (Balance Sheet, Income Statement, Cash-Flow Statement, Statement of Changes in Equity, Notes)	
d	Whether the invoice is consistent with the accounts	

Table 4. The financial transparency definition

The four variables shown in Table 4, are meaningful in projects completed by DCF. Although it does not directly affect the donation amount, it can reflect the public attitude toward the project sponsor. This study developed a Transparency Score (TS) based on these four indicators. Each indicator corresponds to one point. Four points are awarded if four indicators are met. The higher the score, the more complete the materials, the clear and transparent the use of raised funds, and the more transparent the information disclosure of project sponsors.

3.3 Linear regression

From the variables defined in this study, the following multiple linear regression equation can be defined:

$$R = \beta_0 + \beta_1 ND_1 + \beta_2 T_2 + \beta_3 NW_3 + \beta_4 NP_4 + \beta_5 TS_5 + \varepsilon \quad (1)$$

Where:

R is a binary categorical variable, with "1" for "success" and "0" for "failure". For the variables ND, NW, NP and TS, which are positive numerical variables, to eliminate the influence of scale on the results, this study performed natural logarithmic processing on them to eliminate the effect of scale on the regression results. As for the categorical variable T has only two categories: "1" is initiated by an institution or organization, and "0" means an individual. Equation (1) uses a binary logistic regression

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model to explore the effect of the independent variables defined in this study on project success. At the same time, this paper will also analyze the model's ability to predict project success in logistic regression.

3.4 ANN model

This paper will also consider the performance of models. ANN model mimics the way the human brain processes information. A trained ANN model can have memory and knowledge-processing capabilities (Thakial & Arora, 2019). This study uses the BP (Back Propagation) neural network model. BP neural network is a multi-layer feed-forward neural network, mainly using the error backpropagation algorithm and the gradient descent method to obtain the minimum approximation value. It is generally divided into three layers: input, hidden, and output. The basic algorithm is as follows:

$$y_i = 1/[1 + \exp(-\sum_{i=1}^{n} w_{ij}x_i)] \quad (2)$$

$$w_{ij}(k+1) = w_{ij}(k) + \eta\sigma_j x_i + \alpha[w_{ij}(k) - w_{ij}(k-1) \quad (3)$$

Where:

x_i is the sample data input in the j nodes of the $(k-1)$ layer. η represents the learning coefficient of the model and α is the impact coefficient. Then the output equation is equation (4), y_j and d_j are expressed as the actual output value and expected output value of the j node.

$$\sigma_j = y_j(1 - y_j)(d_j - y_j) \quad (4)$$

The hidden layer node is reversely calculated as shown in formula (5), where x_j is the actual output value of the j node.

$$\sigma_j = x_j(1 - x_j)\sum_{i=0}^{m} \sigma_j w_{ij} (5)$$

BP neural network is currently the most widely used neural network model, and it does not necessarily need to rely on a large amount of data for training. Therefore, it is often used in research such as predictive classification (Wang et al., 2020). The general neural network model requires a large number of training parameter settings, and the simple algorithm of the BP neural network model can avoid this step and simplify the operation process. But it also has relative limitations, such as the BP algorithm will bring gradient dispersion phenomenon, and for fewer sample data, this problem is alleviated. Therefore, this research will establish a three-layer BP neural network model. To facilitate comparison, according to formula (1), the input layer of the BP neural network model has five neurons corresponding to five independent variables, the hidden layer is one layer, and the output layer is a binary neuron dependent variable.

At the same time, this study will use the pre-training method to analyze the relevant parameters of the neural network. After the pre-training of the sample, the optimal local parameters of the sample can be obtained, avoiding the gradient dispersion phenomenon caused by excessive iteration. At the same time, the parameter setting is more objective, and the confidence is higher. This study uses Python to train neural networks. The training set is 60% of the total sample, or 420 items, and the test set is 40% or 280 items.

4. RESULTS

4.1 Binary logistic regression

First, this study will use the binary logistic regression model shown in formula (1) to test to validate the RQ1. The variables' descriptive analysis and the results of the Hosmer and Lemeshow test are shown in Table 5.

	N	Minimum	Maximum	Average	Standard Deviation
R	700	0	1	0.19	0.392
T	700	0	1	0.68	0.466
ND	700	3	103429	2683.954	7846.4942
NW	700	915	4278	1735.044	364.2264
NP	700	2	18	7.839	2.1856
TS value	700	0	4	2.148	1.3447
Hosmer and Lemeshow Test	Chi-square	5.998			
	Sig.	0.647			

Table 5. Descriptive Statistical Analysis and Hosmer and Lemeshow Test

As can be seen from the original data in table 5, R and T are binary variables, and the mean of R is 0.19, proving that most sample items are unsuccessful. The mean of T is greater than 0.5, which proves that most projects have NPO support. Whereas ND, NW, and NP have very different value spans in projects. The mean of the TS variable of 2.148 proves that most projects provide at least two pieces of financial transparency information. The Hosmer and Lemeshow test null hypothesis is that the model fits the results better. In this study, Sig is 0.647 to accept the null hypothesis, which proves that the model of this study has a good fit.

			Predicted		
			R		Percentage Correct
	Observed		failure	success	
Step 1	R	failure	530	38	93.31
		success	42	90	68.18
	Overall Percentage				88.57

Table 6. Classification Table

Table 6 shows this study's binary logistic regression model prediction results. As defined in the methodology of this study, an outcome "R" with a value of 1 is "success" and 0 is "failure". The prediction results in this research model have an accuracy of 93.31% for failure and 68.18% for success, and comprehensive prediction accuracy of 88.57%.

Variable	B	S.E.	Wald	df	Sig.	Exp(B)
lnND	0.460	0.127	13.082	1	0.000	1.584
lnNW	-1.721	1.011	2.897	1	0.089	0.179
lnNP	-0.231	0.715	0.104	1	0.747	0.794
lnTS	8.573	1.259	46.329	1	0.000	5284.373
T(1)	0.973	0.410	5.624	1	0.018	2.645
Constant	-3.570	7.297	0.239	1	0.625	0.028
-2 Log likelihood	166.323					
Cox & Snell R Square	0.402					
Nagelkerke R Square	0.648					

Table 7. Variables in the Equation

Table 7 reflects the degree of influence of independent variables on the results of binary logic. Among them, ND, TS and T reject the null hypothesis within the 0-0.05 confidence interval, the coefficients are all positive, and all have significant statistical significance. ND had a positive correlation with results, suggesting that the number of donors can positively influence the success of the DCF project. Of course, this conclusion confirms the existing crowdfunding research on the positive relationship between the number of backers and crowdfunding financing performance (Belleflamme et al., 2014). Researchers generally use “herd behavior” as the theoretical basis for explaining this result. Second, the positive effect of TS on the results confirms the hypothesis of this study that greater financial transparency is more likely to attract donations. In a study on NPO financial transparency, organizations with greater transparency were more likely to attract donations (Ortega-Rodríguez et al., 2020). The coefficient of T is positive, indicating that if the project sponsor is an NPO, it can positively impact the project’s success. Projects initiated by NPOs can increase the project's credibility and influence supporters' motivation.

In addition, within the 0.05-0.1 confidence interval, lnNW had a negative impact on the results. It is contrasted with existing research on the performance of other types of CF financing (Xu et al., 2014). This study found that a higher number of words in the description adversely affected the results. The reason is that this study speculates that the crowdfunding type is donation-based, and too much descriptive text will reduce the willingness of supporters to donate. The value of Cox & Snell R Square is 0.402, which means that the independent variable in this research model explains 40.2% of the dependent variable. The Nagelkerke R Square value was 0.648, reflecting the high statistical significance of the model in this study.

4.2 BP neural network analysis

This research adopts the Keras neural network framework to build a BP neural network model. Keras is an application programming interface (API) for deep learning based on Python. Its primary function is to optimize the model structure and significantly improve the training speed of neural network models (Keras, 2022). In pre-training, this study selects the Rectified Linear Unit (ReLU) function as the activation function of the model neurons in this study. The ReLU function is one of the most commonly used functions in neural network model training. Its most significant advantage is that it is simple to calculate and performs better when the model sample data is linear or close to linear.

Meanwhile, this study adopts cross-entropy as the model’s loss function, and uses adaptive moment estimation (Adam) as the optimization algorithm of the model. The Adam algorithm can dynamically adjust the learning rate for each parameter according to the first-order moment estimation and the second-order moment estimation of the gradient of each parameter by the loss function, so it is convenient to set

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the corresponding parameters better. In this study's pre-training of the BP neural network model, each layer's connection weights and biases are initially randomly generated, the epoch is set to 10, and the model is evaluated after training. This paper evaluates the model's performance by outputting the accuracy of the loss function of the DNN model. The results of the model are shown in Figure 1.

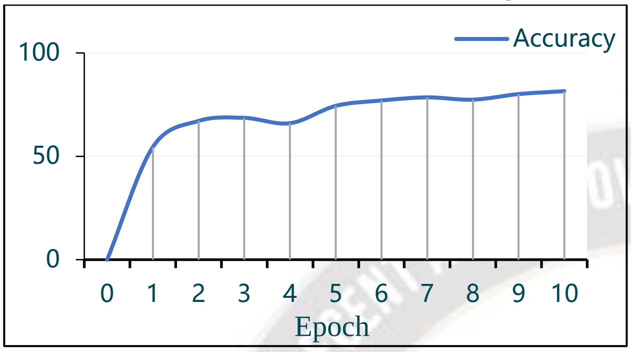

Figure 1. Training accuracy results

Figure 1 shows the pre-training fitting results of the BP neural network model constructed in this research. After the epoch is 2, the fitting degree of the model has nearly reached 67.1%, and tends to be stable in the subsequent epochs. Finally, when the epoch is 10, the accuracy of the BP neural network model reaches 81.5%, indicating that the BP neural network model has a good degree of adaptation to the samples in this study.

According to the pre-training results, this study sets the learning rate to 0.001 in the complete training, the number of iterations to 42, the number of batches per processing to 10, and the loss function to be cross-entropy. Figure 2 shows the loss curve and accuracy of the BP neural network model.

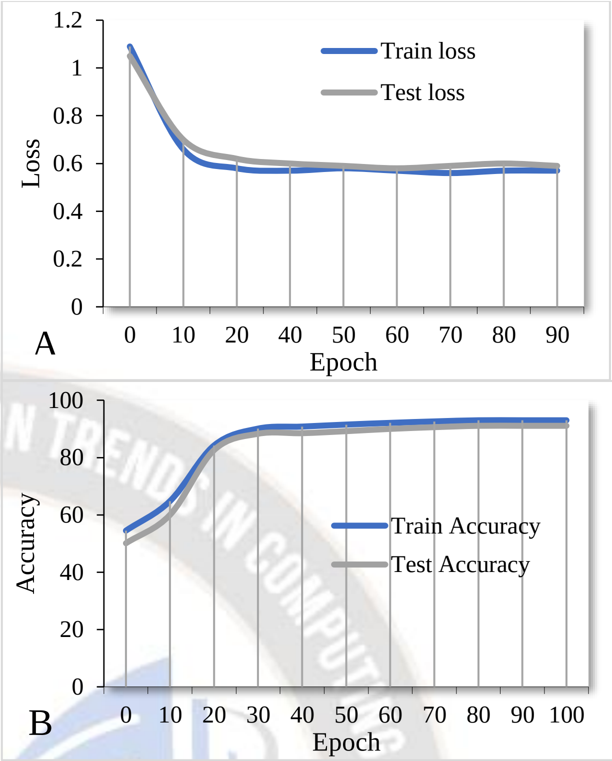

Figure 2. Loss and accuracy curve of the BP neural network model

According to the results shown in Figure 2-A, the change trends of the loss curves of the training set and test set of the BP neural network model are basically the same. The loss value for the test set is 0.7 at epoch 10, which remains stable thereafter, and the loss value for the test set at epoch 100 is 0.59. And Figure 2-B shows the accuracy curves of model training and testing. According to the results in the figure, when the Epoch is 30, the accuracy of the training set reaches 90.1 and begins to converge, while the accuracy of the test set is 88.3% and begins to converge. After 70 rounds of convergence, when the epoch is 100, the accuracy of the training set reaches 93%, and the accuracy of the test set reaches 91.07%. The results in Figure 2 show that the performance of the BP neural model is excellent. At the same time, this study analyzes the model's discriminant accuracy, and the confusion matrix analysis results are shown in Table 8.

	Observed		Predicted		
			R		Percentage Correct
			failure	success	
The actual situation	R	failure	212	15	93.39
		success	10	43	81.13
	Overall Percentage				91.07

Table 8. BP neural network model confusion matrix

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The results of the confusion matrix analysis are shown in Table 8, with a total of 280 items in the test set. The overall prediction accuracy is 91.07%, which is better than the 88.57% accuracy of binary logistic regression in Table 6. Comparing the two models, the prediction accuracy of project failure is about 93%, but the prediction accuracy of project success is very different. The accuracy rate of the BP neural network in successful projects is 81.13%, which is much higher than 68.18% of binary logistic regression, indicating that the BP neural network model has better performance in predicting project success in this study sample.

At the same time, to minimize the impact of different distributions of training samples on the accuracy of model analysis, after comprehensive consideration, this study decided to use a ten-fold cross-check method to test the validity of the model further. In this paper, the sample test set was equally divided into ten parts, and each part was tested separately. The prediction accuracy is used to measure the discriminative performance of the BP neural network model on the project results, which are shown in Figure 3.

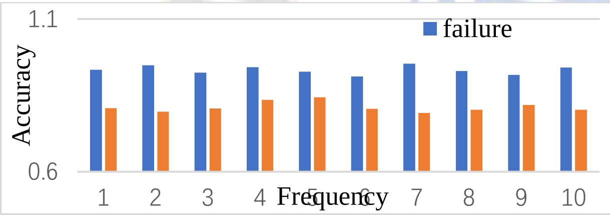

Figure 3. Ten-fold cross-check results

According to Figure 3, there is little difference in the model's predictive ability in each part. In the test of some samples, the accuracy of the model's prediction of project failure is still higher than that of project success. Therefore, this study's prediction performance of the BP neural network model is effective and objective.

Variable	Importance
lnND	0.53
lnNW	-2.71
lnNP	-0.03
lnTS	12.17
T(1)	1.17

Table 9. Importance of independent variables

Table 9 shows the importance of each independent variable of the BP neural network model. The results show significance similar to those of binary logistic regression in Table 7. The number of donors (ND), the Transparency Score (TS) and the type of project sponsor (T) can all positively affect the success of DCF projects, while the number of words (NW) and the number of pictures (NP) DCF project success has a negative impact. And the importance of TS is much greater than other independent variables, which verifies the main conclusion in this study, that is, higher financial transparency can attract donations.

5. FINDINGS DISCUSSION AND CONCLUSIONS

As an emerging online donation method, DCF has recently received much attention. DCF projects are typically not-for-profit projects, so backers usually don't receive any material return. It has changed the traditional donation model and made it easier to participate in charitable causes. This study found that most of the existing studies on DCF focus on donor motivation and project sponsors, and few studies have investigated DCF projects from the perspective of financial transparency. Moreover, most of the project research on environmental and animal protection focuses on offline traditional fundraising projects, and research on online DCF is still lacking.

Therefore, this research pioneered donation crowdfunding projects related to environmental and animal protection, combined with financial transparency of the project, to study the success factors of the project. Through empirical analysis, the results of this study confirm that financial transparency is the most critical factor influencing the success of environmental and animal protection DCF projects. The more financial transparency a project is, the easier it is for the project to be successful. At the same time, this study also confirms that if the project sponsor is an NPO, it increases the project's credibility and positively impacts its success. Second, the number of donors can also be beneficial to project success. In addition, this study found that excessive descriptions of the projects were detrimental to the project's success.

In addition, this study also uses the BP neural network model and the traditional binary logistic regression model for comparative analysis. The results of this study confirm that the BP neural network model can optimize the traditional binary logistic regression model in the successful prediction of DCF, and improve the prediction accuracy to 91.07%. And to a large extent, the prediction accuracy of the project "success" of the binary logistic regression model is optimized. At the same time, this study also conducted a ten-fold cross-check on the BP neural network model, and the results show that the model has good accuracy.

The overall success rate of donation crowdfunding projects related to environmental and animal protection is not high. In addition to the negative factors identified in this study, such as the item's description word count, there must be other, more critical reasons. The inability to investigate further here is one of the limitations of this study. It is of great practical interest to discuss those potential factors in future research to aid the project's environmental and animal protection causes. At the same time, in terms of the financial transparency of DCF projects, the inability to obtain more relevant indicators is also one of the limitations of this study. As the financial transparency of non-profit organizations increases, this study believes that the finances of DCF projects will also become more transparent in the future. This can not only improve the overall quality of the industry, but also improve donors' trust in it. At the same time, it can also contribute to the sustainable development of all public welfare undertakings.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, author- ship, and/or publication of this article.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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REFERENCES

[1] *2020 China Charitable Donation Report*. (2020). http://www.charityalliance.org.cn/news/14364.jhtml

[2] Althoff, T., & Leskovec, J. (2015). Donor retention in online crowdfunding communities: A case study of donorschoose. org. *Proceedings of the 24th International Conference on World Wide Web*, 34–44.

[3] Belleflamme, P., Lambert, T., & Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. *Journal of Business Venturing*, *29*(5), 585–609.

[4] Beltran, J. F., Siddique, A., Abouzied, A., & Chen, J. (2015). Codo: Fundraising with conditional donations. *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology*, 213–222.

[5] Body, A., & Breeze, B. (2016). What are 'unpopular causes' and how can they achieve fundraising success? *International Journal of Nonprofit and Voluntary Sector Marketing*, *21*(1), 57–70.

[6] Buccoliero, L., Bellio, E., Mazzola, M., & Solinas, E. (2015). A marketing perspective to "delight" the "patient 2.0": new and challenging expectations for the healthcare provider. *BMC Health Services Research*, *16*(1), 1–12.

[7] Buttice, V., Colombo, M. G., & Wright, M. (2017). Serial crowdfunding, social capital, and project success. *Entrepreneurship Theory and Practice*, *41*(2), 183–207.

[8] Cheng, C., Tan, F., Hou, X., & Wei, Z. (2019). Success Prediction on Crowdfunding with Multimodal Deep Learning. *IJCAI*, 2158–2164.

[9] Choy, K., & Schlagwein, D. (2016). Crowdsourcing for a better world. *Information Technology & People*, *29*(1), 221–247.

[10] Cockrell, S. R., Meyer, D. W., & Smith, A. D. (2016). Electronic intervention and platforms and their impacts on crowdfunding behaviour. *International Journal of Business Information Systems*, *23*(3), 263–286.

[11] De Buysere, K., Gajda, O., Kleverlaan, R., Marom, D., & Klaes, M. (2012). *A framework for European crowdfunding*.

[12] Dragojlovic, N., & Lynd, L. D. (2014). Crowdfunding drug development: the state of play in oncology and rare diseases. *Drug Discovery Today*, *19*(11), 1775–1780.

[13] Duan, Y., Hsieh, T.-S., Wang, R. R., & Wang, Z. (2020). Entrepreneurs' facial trustworthiness, gender, and crowdfunding success. *Journal of Corporate Finance*, *64*(C), 101693.

[14] Gallo-Cajiao, E., Archibald, C., Friedman, R., Steven, R., Fuller, R. A., Game, E. T., Morrison, T. H., & Ritchie, E. G. (2018). Crowdfunding biodiversity conservation. *Conservation Biology*, *32*(6), 1426–1435.

[15] Ghahramani, Z. (2015). Probabilistic machine learning and artificial intelligence. *Nature*, *521*(7553), 452–459.

[16] Gleasure, R., & Feller, J. (2016). Emerging technologies and the democratisation of financial services: A metatriangulation of crowdfunding research. *Information and Organization*, *26*(4), 101–115.

[17] Greenberg, M. D., Pardo, B., Hariharan, K., & Gerber, E. (2013). Crowdfunding support tools: predicting success & failure. In *CHI'13 extended abstracts on human factors in computing systems* (pp. 1815–1820).

[18] Isa, N. A. M., Irpan, H. M., Bahrom, H. bin, Salleh, A. B. M., & Ridzuan, A. R. bin. (2015). Characteristic affecting charitable donations behavior: Empirical evidence from Malaysia. *Procedia Economics and Finance*, *100*(31), 563–572.

[19] Jiang, C., Pérez-Estébanez, R., & Urquía-Grande, E. (2022). Is Equity Crowdfunding the Leapfrog to Companies' Success? Financial Performance in China. *Computational Intelligence and Neuroscience*, *2022*(C), 7814550.

[20] Jiang, C., Urquía-Grande, E., & Estébanez, R. P. (2021). Research on the performance factors of reward-based crowdfunding: evidence from China. *RAITES*, *7*(15), 10–35.

[21] Korzynski, P., Haenlein, M., & Rautiainen, M. (2021). Impression management techniques in crowdfunding: An analysis of Kickstarter videos using artificial intelligence. *European Management Journal*, *39*(5), 675–684.

[22] Král, P., & Cuskelly, G. (2018). A model of transparency: determinants and implications of transparency for national sport organizations. *European Sport Management Quarterly*, *18*(2), 237–262.

[23] Kubo, T., Veríssimo, D., Uryu, S., Mieno, T., & MacMillan, D. (2021). What determines the success and failure of environmental crowdfunding? *Ambio*, *50*(9), 1659–1659.

[24] Lacan, C., & Desmet, P. (2017). Motivations for participation and e-WOM among supporters of crowdfunding campaigns. In *Strategic innovative marketing* (pp. 315–321). Springer.

[25] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning.

Nature, *521*(7553), 436–444.

[26] Lee, S., Lee, K., & Kim, H. (2018). Content-based success prediction of crowdfunding campaigns: A deep learning approach. *Companion of the 2018 ACM Conference on Computer Supported Cooperative Work and Social Computing*, 193–196.

[27] Lee, Y.-C., Yen, C.-H., & Fu, W.-T. (2016). Improving donation distribution for crowdfunding: An agent-based model. *International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction and Behavior Representation in Modeling and Simulation*, 3–12.

[28] Li, Y., Rakesh, V., & Reddy, C. K. (2016). Project success prediction in crowdfunding environments. *Proceedings of the Ninth ACM International Conference on Web Search and Data Mining*, 247–256.

[29] Li, Y.-M., Wu, J.-D., Hsieh, C.-Y., & Liou, J.-H. (2020). A social fundraising mechanism for charity crowdfunding. *Decision Support Systems*, *129*(C), 113170.

[30] Li, Y.-Z., He, T.-L., Song, Y.-R., Yang, Z., & Zhou, R.-T. (2018). Factors impacting donors' intention to donate to charitable crowd-funding projects in China: a UTAUT-based model. *Information, Communication & Society*, *21*(3), 404–415.

[31] Liu, C.-J., & Hao, F. (2017). Reciprocity belief and gratitude as moderators of the association between social status and charitable giving. *Personality and Individual Differences*, *100*(111), 46–50.

[32] Lundberg, P., Vainio, A., MacMillan, D. C., Smith, R. J., Verissimo, D., & Arponen, A. (2019). The effect of knowledge, species aesthetic appeal, familiarity and conservation need on willingness to donate. *Animal Conservation*, *22*(5), 432–443.

[33] Majumdar, A., & Bose, I. (2017). *Demystifying the factors that impact the success of charitable crowdfunding postings*.

[34] Mano, R. S. (2014). Social media, social causes, giving behavior and money contributions. *Computers in Human Behavior*, *31*(C), 287–293.

[35] Mitra, T., & Gilbert, E. (2014). The language that gets people to give: Phrases that predict success on kickstarter. *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 49–61.

[36] Moritz, A., & Block, J. H. (2016). Crowdfunding: A literature review and research directions. *Crowdfunding in Europe*, 25–53.

[37] Mullainathan, S., & Spiess, J. (2017). Machine learning: an applied econometric approach. *Journal of Economic Perspectives*, *31*(2), 87–106.

[38] Ndeffo Mbah, M. L., & Gilligan, C. A. (2011). Resource allocation for epidemic control in metapopulations. *PLoS One*, *6*(9), e24577.

[39] Neumayr, M., & Handy, F. (2019). Charitable giving: What influences donors' choice among different causes? *Voluntas: International Journal of Voluntary and Nonprofit Organizations*, *30*(4), 783–799.

[40] Ortega-Rodríguez, C., Licerán-Gutiérrez, A., & Moreno-Albarracín, A. L. (2020). Transparency as a key element in accountability in non-profit organizations: A systematic literature review. *Sustainability*, *12*(14), 5834.

[41] Özdemir, V., Faris, J., & Srivastava, S. (2015). Crowdfunding 2.0: the next-generation philanthropy: A new approach for philanthropists and citizens to co-fund disruptive innovation in global health. *EMBO Reports*, *16*(3), 267–271.

[42] Peng, N., Zhou, X., Niu, B., & Feng, Y. (2021). Predicting Fundraising Performance in Medical Crowdfunding Campaigns Using Machine Learning. *Electronics*, *10*(2), 143.

[43] Salido-Andres, N., Rey-Garcia, M., Alvarez-Gonzalez, L. I., & Vazquez-Casielles, R. (2021). When the winner takes it all: online campaign factors influencing the success of donation-based crowdfunding for charitable causes. *International Review on Public and Nonprofit Marketing*, 1–18. https://doi.org/https://doi.org/10.1007/s12208-021-00320-4

[44] Shi, J., Yang, K., Xu, W., & Wang, M. (2021). Leveraging deep learning with audio analytics to predict the success of crowdfunding projects. *The Journal of Supercomputing*, *77*(7), 7833–7853.

[45] Smith, S., Windmeijer, F., & Wright, E. (2015). Peer effects in charitable giving: Evidence from the (running) field. *The Economic Journal*, *125*(585), 1053–1071.

[46] Solomon, J., Ma, W., & Wash, R. (2015). Don't wait! How timing affects coordination of crowdfunding donations. *Proceedings of the 18th Acm Conference on Computer Supported Cooperative Work & Social Computing*, 547–556.

[47] Tan, J., Lu, Y., & Tan, Y. (2021). The Impact of Subscription Reciprocity on Charitable Content Creation and Sharing: Evidence from Twitter on Giving Tuesday. *Management Information Systems Quarterly*, *45*(2), 535–562.

[48] Thakial, S., & Arora, B. (2019). Neural Network Based Prediction Model for Job Applicants. *Journal of Computational and Theoretical Nanoscience*, *16*(9), 3867–3873.

[49] Verhaert, G. A., & Van den Poel, D. (2011). Empathy as added value in predicting donation behavior. *Journal of Business Research*, *64*(12), 1288–1295.

[50] Veríssimo, D., Campbell, H. A., Tollington, S., MacMillan, D. C., & Smith, R. J. (2018). Why do people donate to conservation? Insights from a 'real world'campaign. *PloS One*, *13*(1), e0191888.

[51] Waldron, A., Miller, D. C., Redding, D., Mooers, A., Kuhn, T. S., Nibbelink, N., Roberts, J. T., Tobias, J. A., & Gittleman, J. L. (2017). Reductions in global biodiversity loss predicted from conservation spending. *Nature*, *551*(7680), 364–367.

[52] Wang, W., Zheng, H., & Wu, Y. J. (2020). Prediction of fundraising outcomes for crowdfunding projects based on deep learning: a multimodel comparative study. *Soft Computing*, *24*(11), 8323–8341.

[53] Xu, A., Yang, X., Rao, H., Fu, W.-T., Huang, S.-W., & Bailey, B. P. (2014). Show me the money! An analysis of project updates during crowdfunding campaigns. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 591–600.

[54] Yeh, J.-Y., & Chen, C.-H. (2020). A machine learning approach to predict the success of crowdfunding fintech project. *Journal of Enterprise Information Management*. https://doi.org/https://doi.org/10.1108/JEIM-01-2019-0017

[55] Zainon, S., Atan, R., & Wah, Y. B. (2014). An empirical study

on the determinants of information disclosure of Malaysian non-profit organizations. *Asian Review of Accounting*, *22*(1), 35–55.