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Predicting the fundraising performance of environmental crowdfunding projects: An interpretable machine learning approach

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ABSTRACT

Crowdfunding has become a pivotal fundraising method for environmental organizations. However, the fundraising performance of environmental crowdfunding projects remains subpar, prompting the need for improvements. Effectively addressing this challenge entails the precise prediction of each project's fundraising performance and a comprehensive understanding of the intricate correlations between various features and fundraising success. In response to these imperatives, this study introduces an interpretable framework meticulously designed for predicting the fundraising performance of environmental crowdfunding projects. This comprehensive framework integrates ten theoretically significant features to form the predictive model's feature set. It adopts a diverse array of eight algorithms for training and harnesses SHAP values and ALE plots for insightful post-hoc interpretation, thereby providing valuable insights into the nuanced roles played by these features. Validated on a dataset comprising 3,101 environmental crowdfunding projects from Tencent Charity, the proposed framework outperforms state-of-the-art methods, demonstrating an improvement of 5.9% in predictive performance. Furthermore, the post-hoc interpretation techniques accurately depict the roles of the features. This study carries substantial practical implications for environmental crowdfunding project creators to optimize project design, for crowdfunding platform administrators to enhance platform performance, and for local governments to improve regional environmental governance.

1. Introduction

1.1. Motivation

Crowdfunding has become a popular fundraising model, allowing projects to collect funds from internet users through online crowdfunding platforms (Messeni Petruzzelli, Natalicchio, Panniello, & Roma, 2019). In recent years, environmental organizations have turned to crowdfunding as a promising avenue to secure funds for their projects, leading to the rise of environmental crowdfunding projects. These projects are specifically dedicated to environmental causes and play a crucial role in supporting non-profit organizations engaged in environmental activities (Kubo, Veríssimo, Uryu, Mieno, & MacMillan, 2021). However, compared to

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crowdfunding projects in other domains, the fundraising performance of environmental crowdfunding projects is not as optimistic. For instance, on China's Tencent Charity crowdfunding platform, the achievement rate of fundraising goals and the number of donors for environmental projects are noticeably lower than those in other domains such as poverty alleviation and medical assistance (Ba, Zhao, Zhou, & Song, 2020). Improving the fundraising performance of environmental crowdfunding projects is of great importance. Achieving this goal requires assessing environmental crowdfunding projects' fundraising prospects before launch, which involves predicting their fundraising performance.

Currently, there is no specific framework proposed for predicting environmental crowdfunding projects' fundraising performance. Nevertheless, numerous studies have presented frameworks for predicting general crowdfunding projects' fundraising performance. These frameworks leverage machine learning algorithms, including Decision Tree (DT), Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), Random Forest (RF), Gradient Boosting Decision Tree (GBDT), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Convolutional Neural Networks (CNN), and Deep Cross Attentional Product Network (DCAP), to train predictive models (Al-Qershi, Kwon, Zhao, & Li, 2022; Babayoff & Shehory, 2022; Cheng, Tan, Hou, & Wei, 2019; Etter, Grossglauser, & Thiran, 2013; Greenberg, 2013; Guo, Zhou, Zhan, Zeng, & Zhong, 2020; Tang, Yang, Li, Lian, & Duan, 2023; Wang, Zheng, & Wu, 2020; Yuan, Lau, & Xu, 2016). While these models demonstrate high accuracy in forecasting fundraising performance, they suffer from a significant drawback for decision-makers involved in project design and launch: a lack of interpretability. More precisely, due to the complexity of the algorithms employed, these models struggle to elucidate their internal mechanisms in a straightforward manner and fail to clarify the relationships between predictive features and outcomes (Hofman, Sharma, & Watts, 2017). They are often referred to as "black-box" models, as they do not reveal crucial factors essential for creators to enhance the design of crowdfunding projects (Suvorova, 2021).

To achieve the objective of improving the fundraising performance of environmental crowdfunding projects, the present study aims to address both robust prediction and human comprehension by adopting interpretable machine learning methods (Lundberg & Lee, 2017). Interpretable machine learning refers to methods that enable the decision-making process of predictive models to be easily understood by humans (Molnar, 2020). Its goal is to provide explanations for the predictive process and decisions while maintaining predictive model performance (Suvorova, 2021). Compared to traditional modeling approaches, the unique aspect of interpretable machine learning-based modeling is an additional step for model interpretation. This step involves employing post-hoc interpretation techniques, such as SHAP values and ALE plots, to visualize the roles of features within black box models. Building upon this rationale, the development of a predictive framework rooted in interpretable machine learning equips creators of environmental crowdfunding projects with the means to comprehend the reasoning process behind predictive models. This understanding empowers them to devise strategies aimed at enhancing the fundraising performance of such projects.

1.2. Research objectives

We aim to develop an interpretable predictive framework for forecasting the fundraising performance of environmental crowdfunding projects based on the interpretable machine learning approach. This framework consists of two parts: the first part focuses on constructing a feature set and selecting algorithms to train a highly accurate predictive model, while the second part concentrates on creating a pathway to interpret the predictive model. To achieve the construction of this framework, the study has two specific objectives:

- To explore how to accurately predict the fundraising performance of environmental crowdfunding projects.
- To explore how to interpret the aforementioned predictive model using post-hoc interpretation techniques.

To accomplish the first objective, we will create a feature set that incorporates theoretically grounded features identified through extensive research on the determinants of crowdfunding projects' fundraising performance. These features will be integrated with algorithms commonly employed in existing prediction methods for crowdfunding projects' fundraising performance to train the predictive model. For the second objective, we will review commonly used post-hoc interpretation techniques for predictive models in social science research. We will carefully select well-established techniques to design a pathway for model interpretation, facilitating a deeper understanding of the factors influencing the model's predictions.

The subsequent sections are organized as follows: Section 2 conducts a comprehensive review of three distinct categories of scholarly literature, encompassing factors influencing the fundraising performance of crowdfunding projects, methodologies for forecasting crowdfunding projects' fundraising performance, and post-hoc interpretation techniques applied to predictive models in the realm of social science research. Section 3 presents a detailed explanation of the proposed framework, outlining the steps involved in constructing the feature set, selecting appropriate algorithms, evaluating trained models, and integrating the interpretable machine learning approach. Section 4 conducts experiments on real datasets to assess the predictive performance of the proposed framework and to test its effectiveness in enhancing the interpretability of predictive models. Section 5 summarizes the theoretical and practical implications of our work. Section 6 concludes the paper and discusses the limitations of this study.

2. Related work

As demonstrated in our research objectives, this section reviews three groups of related works. The first group summarizes the determinants of crowdfunding projects' fundraising performance. The second group introduces the prediction methods for crowdfunding projects' fundraising performance. The third group summarizes post-hoc interpretation techniques for predictive models in social science research.

2.1. Determinants of crowdfunding projects' fundraising performance

In previous research on the determinants of crowdfunding projects' fundraising performance, scholars have identified a series of project features that significantly impact fundraising performance using classical theories such as signal theory, psychological distance theory, elaboration likelihood model, heuristic theory, persuasion theory, and emotional contagion theory. These features can be broadly categorized into three types: structural features, content features, and agency features. Below, we will delve into each of these categories in detail.

Firstly, studies focusing on structural features aim to elucidate the relationship between the metadata associated with crowdfunding projects and their fundraising performance. Commonly considered metadata elements encompass the project's fundraising goal, target domain, and duration.

The *fundraising goal* represents the monetary amount that a crowdfunding project aims to raise. Following signal theory, Koch and Siering (2019) argued that the fundraising goal, as an indicator of a project's complexity, positively correlates with potential donors' perception of project risk, thereby negatively affecting fundraising performance. This assertion is substantiated by the research conducted by Zhang, Tao, Ji, Wang, and Sörensen (2023), which revealed a negative correlation between fundraising goals and the probability of project success, based on the analysis of 92,753 cancer crowdfunding projects on the GoFundMe platform.

The *target domain* pertains to the thematic focus of the activities that will be funded by the project. Drawing from psychological distance theory, Weinmann (2019) demonstrated that the target domain, linked to the psychological distance of the cause, impacts the willingness of potential donors to take action in addressing the issue, thereby affecting their fundraising performance. In alignment with this perspective, Kim, Kang, and Engel (2022) found that projects related to medical, financial assistance, and physical needs achieved higher goal attainment rates compared to other project types, based on an analysis of 889 projects on the South Korean charity crowdfunding platform, Happy Bean.

The *project duration* represents the time window that the creator has set for the project to raise funds. While a longer project duration provides more time for potential donors to familiarize themselves with project features (Lagazio & Querci, 2018), signal theory suggests that it also signals low confidence and low urgency among project creators (Ba et al., 2020; Mollick, 2014), resulting in a complex nonlinear relationship between project duration and fundraising performance. Confirming this argument, Chen, Zhou, Jin, and Chen (2023) identified a U-shaped relationship between project duration and goal attainment rate, raised amount, and the number of donors, based on an analysis of 754 projects on the Qingsongchou platform.

Secondly, research concentrating on content features endeavors to elucidate how the attributes of the project description impact crowdfunding projects' fundraising performance. Common project description features include text length, complexity, logicality, positivity, and image count.

Text length quantifies the number of words used to delineate the project's objectives or implementation plan. Aligned with signal theory, Yang, Li, Calic, and Shevchenko (2020) posited that text length, as a reflection of the project's quality and preparedness, positively influences potential donor confidence in project success, thereby enhancing fundraising performance. Consistent with this perspective, Zhang, Liu, Wang, Zhao, and Zhang (2022) discovered a positive correlation between project description length and the goal attainment rate, donor participation, and funding speed. These findings emerged from an analysis of 103,582 projects on the Indiegogo platform.

Text complexity refers to the level of sophistication and difficulty in the project description or argumentation. The impact of text complexity on fundraising performance is multifaceted. Drawing from heuristic theory, Markowitz and Shulman (2021) posited that text complexity, serving as a heuristic cue, heightens potential donors' perception of project quality, thus positively influencing fundraising performance. Conversely, following the elaboration likelihood model, Li, Wu, and Zhou (2023) argued and substantiated that high text complexity, hindering potential donors' comprehension, is inversely related to project persuasiveness, negatively affecting fundraising performance.

Text logicality pertains to the coherence and rationality of the project description's argumentation. As per persuasion theory, Wu, Zhang, and Xiao (2022) argued that text logicality, addressing individuals' need for reasoned evaluation, positively correlates with project credibility, thus enhancing fundraising performance. This assertion is corroborated by Wang, Chen, Zhu, and Wang (2016), who identified a significant positive correlation between logical reasoning in project arguments and the fundraising success rate of fashion crowdfunding projects, based on an analysis of 128,345 projects on Kickstarter.

Text positivity refers to the level of positivity in the tone adopted by the project creator when describing the project. Rooted in the emotional contagion theory, Zhao, Zhou, and Zhao (2022) posited that a positive tone employed in project descriptions has the capacity to evoke similar emotions in potential donors, thereby impacting fundraising performance. However, it is noteworthy that the precise mechanisms through which text positivity affects fundraising performance are intricate. Zhou, Lu, Fan, and Wang (2018) contended that a moderate use of a positive tone could convey the project creator's confidence, while excessive use of a positive tone may diminish the project's credibility. To substantiate this perspective, they identified an inverted U-shaped relationship between the positivity of project descriptions and success rates. These findings emerged from an analysis of 151,752 projects on the Kickstarter platform.

Image count refers to the number of illustrations used to complement textual content in the project description. In accordance with persuasion theory, Xu (2018) argued that image count, as a pivotal determinant of persuasion, enhances information transmission, thus positively impacting fundraising performance. This viewpoint is corroborated by Yang et al. (2020), who observed that crowdfunding projects featuring more images attracted higher amounts of funding and a greater number of donors, based on an analysis of 13,622 technology crowdfunding projects on Kickstarter.

Finally, research focusing on agency features seeks to explain crowdfunding project fundraising performance through the attributes of the entities associated with the project. Prominent entity characteristics include organization age and manager experience.

Organization age signifies the duration of the existence of the company or nonprofit organization initiating the crowdfunding project. The influence of organization age on fundraising performance is nuanced. From a signal theory perspective, Ralcheva and Roosenboom (2020) posited and verified that a young organization age signals the potential for upward growth in the project creator, consequently enhancing the project's fundraising performance. Conversely, Prokop and Wang (2022) argued and substantiated that an advanced organization age signals the project creator's wealth of experience, thereby boosting the project's fundraising performance.

Manager experience refers to the project leader's expertise in related fields or industries. According to the elaboration likelihood model, Allison, Davis, Webb, and Short (2017) argued that managers' industry experience, serving as a source of human capital and credibility, can instill donors' trust in the project, ultimately leading to higher fundraising performance. This perspective is supported by Barbi and Mattioli (2019), who found that the professional experience of team members contributed to increased funding for Crowdcube projects, based on an analysis of data from 521 projects.

Drawing from the comprehensive review of these determinants, we can discern several project features that hold significant theoretical relevance to crowdfunding performance. These features will be thoughtfully incorporated into the proposed framework, thereby enhancing the predictive model's performance for forecasting environmental crowdfunding projects' fundraising performance.

2.2. Prediction methods for crowdfunding projects' fundraising performance

Currently, prediction methods for crowdfunding projects' fundraising performance can be categorized into three main groups: linear model-based methods, machine learning-based methods, and deep learning-based methods.

Firstly, linear model-based prediction methods for crowdfunding projects' fundraising performance often rely on Logistic regression (LR) as a fundamental approach. For example, Mitra and Gilbert (2014) employed LR along with 11 metadata features (e.g., fundraising goal, target domain, update frequency), and the occurrence count of 4440 phrases in the project description, resulting in a predictive model with an impressive error rate of 2.24% on the Kickstarter dataset. Similarly, Song, Berger, Yosipof, and Barnes (2019) utilized LR in conjunction with 10 metadata features (e.g., fundraising goal, duration, country), and the occurrence count of 26 phrases in the project description, achieving a predictive model with an accuracy of 91% on the Kickstarter dataset. Kaminski and Hopp (2020) considered Doc2Vec vectors of text content in project descriptions, speech, and videos as features in their LR model, leading to a predictive model with an F1 score of 0.78 on the Kickstarter dataset.

Secondly, machine learning-based prediction methods for crowdfunding projects' fundraising performance often employ traditional weak classifiers or ensemble algorithms to train the model. Common weak classifiers include DT, SVM, and MLP, while popular ensemble algorithms mainly consist of RF, GBDT, XGBoost, and LightGBM. For instance, Greenberg (2013) utilized DT with metadata features such as fundraising goal and target domain, alongside textual data features like the sentiment of the description and number of sentences, resulting in a predictive model with an accuracy of 68% on the Kickstarter dataset. Similarly, Etter et al. (2013) employed SVM with features like the fundraising goal and fundraisers' tweet data, achieving a predictive model with an accuracy of 76% on the Kickstarter dataset. Wang et al. (2020) leveraged MLP with features such as the fundraising goal, country, LDA topics, and duration, resulting in a predictive model with an F1 score of 0.921 on the Kickstarter dataset. Yuan et al. (2016) used RF with the fundraising goal and LDA topics as features, obtaining a predictive model with an F1 score of 0.785 on the Dreamore and Zhongchou datasets. Furthermore, Guo et al. (2020) implemented GBDT with features like the fundraising goal, title length, target domain, and duration, successfully achieving a predictive model with an F1 score of 0.71 on the Kickstarter dataset. Al-Qershi et al. (2022) utilized XGBoost with metadata features such as the fundraising goal, the number of videos, and the target domain, in combination with LIWC word frequencies, resulting in a predictive model with an F1 score of 0.818 on the Kickstarter dataset. Lastly, Babayoff and Shehory (2022) adopted LightGBM with metadata features like the fundraising goal, the number of videos, the number of images, the fundraiser's project experience, and the target domain, combined with LIWC word frequencies, which led to a predictive model with an outstanding F1 score of 0.962 on the Kickstarter and Indiegogo datasets.

Lastly, deep learning-based prediction methods for crowdfunding projects' fundraising performance often utilize CNN and DCAP algorithms to train the model. For example, Cheng et al. (2019) used CNN, combining project description text vectors and image vectors, to achieve a predictive model with an F1 score of 0.7534 on the Kickstarter dataset. Tang et al. (2023) employed DCAP, combining project description text vectors and image vectors, to achieve a predictive model with an F1 score of 0.727 on the Kickstarter dataset.

In conclusion, several algorithms have exhibited remarkable effectiveness and relevance in forecasting crowdfunding outcomes, rendering them highly suitable for our specific environmental crowdfunding contexts. Thus, we will seamlessly integrate these aforementioned algorithms into our forthcoming framework to achieve enhanced predictive performance.

2.3. Post-hoc interpretation for predictive models in the social sciences

Currently, post-hoc interpretation techniques for social science prediction models can be broadly categorized into two main types: feature importance evaluation and feature effect visualization.

Firstly, feature importance evaluation involves assessing the contribution or importance of various features to the model's prediction outcomes. Commonly used techniques for feature importance evaluation include tree-based feature importance, SHapley

Additive exPlanations (SHAP) values, and permutation importance. *Tree-based feature importance* is an evaluation method embedded within decision tree-related algorithms, indicating the overall decrease in the impurity of features at decision tree nodes (Zhou & Hooker, 2020). For instance, Al-Qershi et al. (2022) trained a predictive model for crowdfunding project performance using the XGBoost algorithm and subsequently conducted feature importance evaluation through the algorithm's built-in feature importance technique. The results highlighted the fundraising goal as the most critical factor. While tree-based feature importance is widely used, it is limited to tree models. *SHAP values*, on the other hand, reveal the marginal contribution of a feature to the prediction outcome after its inclusion in the model (Lundberg & Lee, 2017). For example, Zhang, Wu, Qu and Chen (2022) trained a predictive model for company financial distress using the LightGBM algorithm and then employed SHAP values to evaluate feature importance. The findings emphasized the growth rate of operating profit as the most influential feature. Unlike tree model feature importance, SHAP values are model-agnostic, applicable to interpret predictions from all classifiers. *Permutation importance* is a simpler approach that assesses the importance of features by randomly permuting the values of each feature and measuring the impact on the model's performance (Altmann, Toloşi, Sander, & Lengauer, 2010). It evaluates how much the model's performance decreases when a specific feature's values are randomly shuffled. For instance, Xenochristou, Hutton, Hofman, and Kapelan (2021) trained a predictive model for household water demand using RF and applied permutation importance to identify the most critical feature—the number of occupants—by observing the highest performance drop. Although permutation importance is also model-agnostic, it is less commonly employed compared to SHAP values.

Secondly, feature effect visualization entails using visualization techniques to depict changes in the prediction outcome caused by feature variations. Common visualization techniques for feature effect visualization include the Partial Dependence (PD) plot, Accumulated Local Effects (ALE) plot, and Local Interpretable Model-agnostic Explanations (LIME) plot. The *PD plot* and *ALE plot* aim to visualize the relationship between predictive features and the prediction results (Apley & Zhu, 2020). For instance, Python et al. (2021) trained a predictive model for terrorist events using XGBoost and utilized the ALE plot to visualize the relationship between population density, economic level, and the probability of event occurrence. Similarly, Chen, Wang, Zhang, Wang, and Peng (2021) developed a stacked model for predicting consumer purchases of travel services and employed the PD plot to visualize the relationship between service ratings and the probability of purchase. On the other hand, the *LIME plot* serves as a local explanation method, elucidating prediction results for individual samples (Apley & Zhu, 2020). For example, Beranová, Joachimiak, Kliegr, Rabby, and Sklenák (2022) trained a neural network for predicting paper citation levels and then employed the LIME plot to present the effects of different predictive features on a representative sample.

In conclusion, post-hoc interpretation techniques have gained significant traction in the realm of predictive models within the social sciences. The selected techniques will be seamlessly integrated into the proposed framework, affording valuable insights into the interpretation of the predictive model for environmental crowdfunding projects' fundraising performance.

3. Proposed framework

This section introduces the structure of the proposed framework (Fig. 1) in five parts: The first part is dedicated to defining the task of the predictive model, encompassing the determination of the outcome variable; The second part elaborates on the feature set and outlines the systematic pathway for feature extraction; The third part carefully selects the appropriate algorithms for the model training process; In the fourth part, various evaluation metrics are presented to assess the model's performance; Finally, the fifth part elucidates the approach for post-hoc model interpretation, facilitating a deeper understanding of the model's predictions.

3.1. Problem formulation

We define the task of predicting the fundraising performance of environmental crowdfunding projects as a binary classification problem, where projects are categorized into "high fundraising performance" and "low fundraising performance," and a classification model is trained accordingly. Formulating the problem as a classification task offers two significant advantages: Firstly, classification tasks are well-suited for employing powerful algorithms, such as SVM and MLP. Secondly, classification tasks can enhance predictive performance, especially when dealing with skewed data.

In the context of donation-based crowdfunding, initiated projects invariably proceed to completion regardless of the amount raised, as no minimum donation threshold is mandated (Chen et al., 2023). Fundraising performance is therefore defined as the "*fundraising success rate*", that is, the ratio of the funds raised to the fundraising goal,[1] a metric in alignment with established research (Ba, Zhao, Song, & Zhu, 2021, 2022; Chen et al., 2023; Kubo et al., 2021; Zhang, Xue, Li, Li, & Liu, 2021). To facilitate integration with the classification algorithm, this metric will be discretized into a binary variable.

We have chosen the 50% threshold for discretization. Specifically, projects surpassing a fundraising success rate of 50% will be designated as 1, while those at or below 50% will be assigned a value of 0. The choice of 50% as a threshold, rather than 100%, is based on the fact that environmental crowdfunding projects often have relatively large fundraising goals, and achieving a 100% fundraising success rate is rare. According to a 2020 survey, more than half of Tencent Charity's environmental crowdfunding projects did not achieve a fundraising success rate of over 50% (Ba et al., 2020). This means that projects with a fundraising success rate of more than 50% already demonstrate high fundraising performance. Predicting whether the fundraising success rate of environmental

[1] Some projects have a fundraising goal of 0. To calculate the fundraising success rate, we use the fundraising goal plus 1 as the denominator.

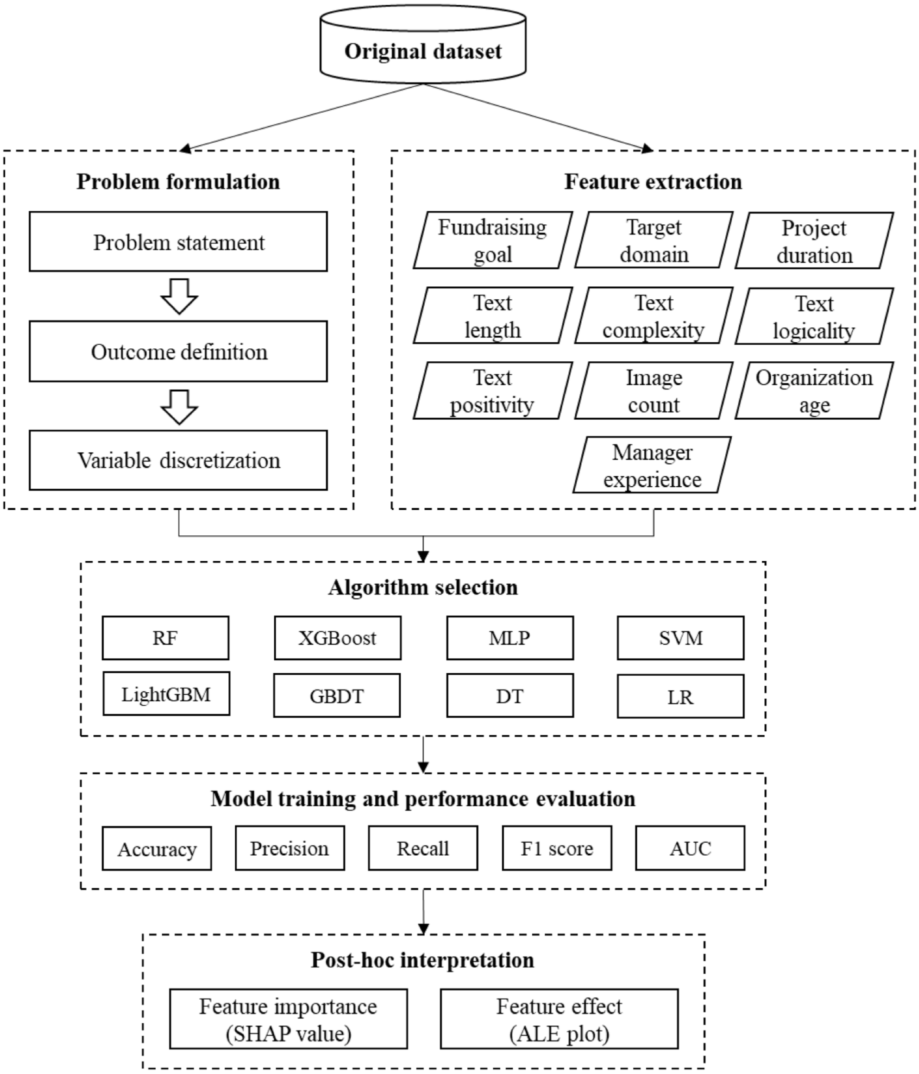

Fig. 1. Proposed framework.

crowdfunding projects can exceed 50% holds significant practical value for project creators.

3.2. Feature extraction

After formulating the problem, the proposed framework outlines a pathway for feature extraction. We focus on ten features mentioned in Section 2.1, namely, fundraising goal, target domain, project duration, text length, text complexity, text logicality, text positivity, image count, organization age, and manager experience. The strategies for feature extraction are discussed as follows:

(1) Fundraising goal is quantified as the targeted amount the environmental crowdfunding project aims to raise.
(2) Target domain is identified as the dominant topic in the project description, which is extracted using Latent Dirichlet Allocation (LDA) topic modeling (Blei, Ng, & Jordan, 2003). In each project description text, the dominant topic is characterized by having the highest probability.
(3) Project duration is measured as the number of days between the start date and the end date of the fundraising (Ba et al., 2021, 2022).
(4) Text length is determined by the number of Chinese characters in the project description.
(5) Text complexity is assessed using the Fog index applied to the project description text (Flesch, 1948). This measurement process is carried out by the "cntext" module, which calculates the Fog index for Chinese text by weighting two key indicators: the "average number of words per sentence" and the "proportion of adverbs and conjunctions in sentences." A higher value indicates greater complexity and reduced readability.

(6) Text logicality is measured by the proportion of connective and causal words in the project description text (Wang et al., 2016). The proportions of these two types of words can be calculated using the Chinese text analysis software "TextMind." A higher proportion of these words indicates stronger logicality.
(7) Text positivity is measured by the degree of positive sentiment in the project description text, calculated using the "xmnlp" module. The results range from 0 to 1, with a higher value indicating a higher level of positive sentiment in the text.
(8) Image count is determined by the number of images present in the project description.
(9) Organization age is calculated as the number of years between the establishment of the fundraising organization and the initiation of the crowdfunding project.
(10) Manager experience is coded based on their work experience. In the context of environmental crowdfunding projects, managers typically possess work experience in government agencies, research institutions, private enterprises, or non-governmental organizations (NGOs). Among these, managers with government work experience are often regarded as more authoritative. Consequently, if project managers have prior experience in government roles, the projects are assigned a value of 1; otherwise, they receive a value of 0.

3.3. Algorithm selection

For model training, the proposed framework selects eight algorithms mentioned in Section 2.2 as the classifiers, including LR, DT, SVM, MLP, RF, GBDT, XGBoost, and LightGBM. These algorithms have been proven to accurately predict the fundraising performance of crowdfunding projects (Al-Qershi et al., 2022; Babayoff & Shehory, 2022; Cheng et al., 2019; Etter et al., 2013; Greenberg, 2013; Guo et al., 2020; Tang et al., 2023; Wang et al., 2020; Yuan et al., 2016). We do not adopt deep learning algorithms as classifiers, as they are more suitable for features such as word vectors and image vectors, which do not match the feature set proposed in the framework.

The optimal hyperparameters of these algorithms were determined using a random search technique, which randomly combines hyperparameter values within specified ranges and selects the combination with the best predictive performance (Bergstra & Bengio, 2012). Compared to other tuning techniques like grid search and Bayesian optimization, random search is more efficient and requires fewer computational resources (Yu & Zhu, 2020).

3.4. Performance metrics

The framework utilizes five common evaluation metrics to assess model performance: Accuracy, Precision, Recall, F1 score, and AUC. In binary classification tasks, the model's predictions can be represented by a 2 × 2 confusion matrix (see Table 1), consisting of TP (true positive), FN (false negative), FP (false positive), and TN (true negative).

Accuracy measures the proportion of correctly predicted samples out of the total samples and is calculated as:

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \tag{1}$$

Precision, Recall, and F1 score focus on specific class predictions. Precision evaluates the proportion of true positive samples among the predicted positive samples:

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall evaluates the proportion of successfully predicted positive samples among all true positive samples:

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

The F1 score, the harmonic mean of Precision and Recall, balances both precision and recall, providing a comprehensive assessment:

$$F1\ score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

AUC (Area Under the Curve) represents the area under the ROC (Receiver Operating Characteristic) curve, plotting Recall against 1-Specificity. A higher AUC indicates better predictive performance:

$$Specificity = \frac{TN}{FP + TN} \tag{5}$$

These metrics collectively gage the model's effectiveness in predicting fundraising performance.

3.5. Post-hoc interpretation

Based on the literature review in Section 2.3, the proposed framework offers a comprehensive pathway for post-hoc interpretation, encompassing two essential steps: feature importance evaluation and feature effect visualization.

Table 1
Confusion matrix for binary classification tasks.

		Predicted values	
		Positive	Negative
Actual values	Positive	TP (Ture Positive)	FN (False Negative)
	Negative	FP (False Positive)	TN (Ture Negative)

Firstly, feature importance evaluation is accomplished using SHAP values within the proposed framework. SHAP values offer detailed insights into the individual contribution of each feature to the prediction, considering what would be expected in the absence of that feature. The selection of SHAP values over other commonly used techniques, such as tree-based feature importance and permutation importance, is based on two primary reasons: Firstly, SHAP values are model-agnostic, enabling explanations for predictions across diverse algorithms (Lundberg & Lee, 2017). Secondly, they have been widely employed and validated in various studies, attesting to their effectiveness in model interpretation.

Secondly, feature effect visualization is achieved through ALE plots within the proposed framework. ALE plots provide valuable insights into the dynamic changes in predictions as feature values vary, facilitating a comprehensive understanding of a feature's impact on the model's output. While several model interpretation methods are available to demonstrate the direction of features' effects on the target variable, such as PD plots and LIME plots, ALE plots are chosen in this study for their distinct advantages: Firstly, LIME is a local explanation method focused on explaining predictions for individual samples, while ALE plots elucidate the impact of features on predictions across the entire dataset. Secondly, PD plots, while also providing explanations at the dataset level, strictly assume independence between features, whereas ALE plots can accurately deliver model explanations even in the presence of interdependent features (Lucas, 2020).

4. Experiments and results

This section presents the experimental results of the proposed framework, consisting of four main parts: First, the dataset for experiments is introduced; Second, the experimental setup is outlined; Third, the predictive performance of the proposed framework is discussed, accompanied by a comparison with state-of-the-art methods; Finally, the model interpretation results are presented. Through a thorough examination of these components, we aim to validate the effectiveness and efficiency of our proposed approach.

Fig. 2. The obtained information of each environmental crowdfunding project.

4.1. Dataset

Having proposed an interpretable framework for predicting the fundraising performance of environmental crowdfunding projects, we proceeded to construct a dataset for experiments. The original data on environmental crowdfunding projects was collected on the Nature Conservation section of the Tencent Charity Platform. The Tencent Charity Platform holds the distinction of being the first online charity crowdfunding platform approved by the Ministry of Civil Affairs in China (Ba et al., 2021). It has outperformed other crowdfunding platforms in terms of total funds raised, number of donors, number of projects, and business scope (Ba et al., 2020).

Within the Nature Conservation section of the Tencent Charity Platform, we identified a total of 3111 crowdfunding projects had closed fundraising. The collected information for each project encompasses the description text, description image, organization name, manager profile, fundraising goal, amount raised, start date and end date (as depicted in Fig. 2) .[2] Considering that there were many missing values in 10 projects, we excluded those projects, resulting in a total of 3101 projects with complete information.

Based on the original dataset, we conducted measurements of the outcome variable and feature extraction in accordance with the proposed framework. Initially, we calculated the fundraising success rate, referred to as "fundraising performance," for each project based on the "amount raised" and "fundraising goal." Subsequently, we discretized this indicator into a binary variable, resulting in 1808 positive samples (assigned a value of 1) and 1293 negative samples (assigned a value of 0) in our dataset.

Following that, we extracted features from the project information we collected. The fundraising goal was directly sourced from the original data. The project duration was deduced from the "start date and end date." Additionally, various features were extracted from the "description text" in the original data, including the target domain, text length, text complexity, text logicality, and text positivity. It's noteworthy that five distinct target domains were identified and extracted from the description text using LDA modeling, namely Species Conservation, Marine Conservation, Urban Environment, Stray Animals, and Environmental Education (as elaborated in Table A1). Furthermore, the image count was computed by counting the number of images in the project description. To determine the organization age, we used the "organization name" to retrieve the establishment time of the organization from the "China Charity" official website. As for manager experience, we coded the relevant data based on information from the "manager profile."

For a comprehensive overview of these features, please consult Table 2, which provides detailed descriptive statistics.

4.2. Experiment setup

To ensure optimal model fitting, we applied four types of transformations to the dataset. Firstly, we employed one-hot encoding for the categorical feature "target domain." This technique creates binary features for each category of the variable. In our study, the target domain feature yielded five binary features: species conservation, marine protection, urban environment, stray animals, and environmental education. Each project is assigned a value of 1 in only one binary feature, while the remaining features are set to 0. Secondly, we identified and eliminated outliers in certain features. This step primarily targeted features that exhibited significant outliers, such as fundraising goal, text complexity, text logicality, image count, and text length. Outliers were defined as observations that exceeded "mean + 3 standard deviations" or fell below "mean - 3 standard deviations." Next, we applied a natural logarithm transformation to features with large scales, namely the fundraising goal and description length. This transformation addresses potential deviations from normality in the data distribution of these features. Finally, we normalized all continuous features to scale them between 0 and 1. This normalization process ensures that the model is not biased by differences in feature scales.

Following the data transformation, we split the dataset into training and testing sets following the 7:3 rule, with 70% of the data randomly selected for training the model and the remaining 30% kept for validating its performance. During the hyperparameter tuning process, we employed stratified 5-fold cross-validation to assess the predictive performance of different hyperparameter combinations. By utilizing stratified 5-fold cross-validation instead of directly using the test set to evaluate hyperparameter combinations, we effectively avoided "overfitting to the test set", which refers to a situation where the model performs well only on the test set but lacks true generalization capability (Lones, 2021). This approach ensures a more robust evaluation of the model's predictive performance. Following these steps, we identified the optimal hyperparameter combinations for the eight algorithms (see Table A2).

4.3. Model evaluation

4.3.1. Performance of the proposed framework

After conducting hyperparameter tuning, the selected algorithms were fitted to the training set using the optimal hyperparameter configurations, resulting in predictive models for environmental crowdfunding projects' fundraising performance. To evaluate the performance of these models, they were applied to the testing set, and various metrics such as Accuracy, Precision, Recall, F1 score, and AUC were computed and presented in Table 3. The analysis of the table led to two key observations:

Firstly, the proposed framework exhibited excellent model performance, with half of the algorithms exceeding 0.8 in predictive performance. This indicates that the feature set proposed in our framework is highly suitable for predicting the fundraising performance of environmental crowdfunding projects. Such results are not surprising, as each predictive feature's relationship with the fundraising performance is well-founded in theory.

[2] Tencent Charity Platform provides two access points: one through a WeChat mini program and the other through a web page. The majority of our data was collected from the WeChat mini program, with only the fundraising goal, amount raised, start date, and end date being sourced from the web interface.

Table 2
The descriptive statistics of features.

Features	Mean	SD	Min	Max
Fundraising goal	412,859.60	1230,519.00	0.00	30,000,000.00
Target domain:				
Species conservation	0.23	0.42	0.00	1.00
Marine protection	0.12	0.32	0.00	1.00
Urban environment	0.31	0.46	0.00	1.00
Stray animal	0.18	0.38	0.00	1.00
Environmental education	0.18	0.38	0.00	1.00
Project duration	1062.55	607.21	5.00	7822.00
Text length	1516.67	818.14	60.00	6074.00
Text complexity	24.48	13.52	5.49	520.04
Text logicality	0.07	0.02	0.00	0.16
Text positivity	0.70	0.30	0.00	1.00
Image count	8.89	4.82	1.00	61.00
Organization age	19.96	10.15	0.93	40.33
Manager experience	0.07	0.26	0.00	1.00

Table 3
Performance of models fitted by different algorithms.

Algorithms	Accuracy	Recall	Precision	F1 score	AUC
LR	0.679	0.640	0.682	0.638	0.640
DT	0.748	0.740	0.740	0.740	0.740
SVM	0.741	0.734	0.733	0.733	0.734
MLP	0.672	0.633	0.673	0.630	0.633
RF	0.896	0.883	0.904	0.890	0.883
GBDT	**0.899**	**0.887**	**0.905**	**0.894**	**0.887**
XGBoost	0.879	0.875	0.875	0.875	0.875
LightGBM	0.890	0.885	0.889	0.887	0.885

Secondly, among all the algorithms, GBDT achieved the best model performance. Specifically, the AUC of the model fitted by GBDT reached 0.887, surpassing the second-ranking algorithm (LightGBM) in terms of AUC by 0.2%. This indicates that GBDT is particularly well-suited for discovering patterns in environmental crowdfunding project data, making it a preferred choice for this task.

Overall, the results demonstrate the effectiveness of the proposed framework's feature set in predicting the fundraising performance of environmental crowdfunding projects, with GBDT emerging as the most suitable algorithm for this predictive task.

To ensure the reliability of the model evaluation results, we performed 50 rounds of stratified 10-fold cross-validation on the entire dataset to obtain the performance scores (AUC) distribution for the eight models (Lones, 2021), as shown in Table 4. From the table, GBDT consistently achieved the highest mean performance score. Additionally, the *t*-test results (shown in the 6th column of Table 4) indicate that the difference in performance scores between GBDT and the other models is statistically significant ($p<0.01$).

4.3.2. *Comparison with state-of-the-art methods*

To further bolster confidence in our proposed framework and underscore its potential advantages, we conducted an exhaustive comparative analysis against state-of-the-art methods. The prevailing literature primarily focuses on forecasting the fundraising performance of crowdfunding projects through their project description text. To derive predictive features from this text, established techniques such as LDA topic modeling, TF-IDF vectorization, LIWC term frequency, and Doc2vec have been employed (Al-Qershi et al., 2022; Chen & Shen, 2019; Du, Du, Wang, & Fan, 2021; Kaminski & Hopp, 2020; Yuan et al., 2016). Therefore, we selected these methods to extract features from the project description text and combined them with GBDT, the optimal algorithm identified earlier, to train our baseline models. Each of these baseline models is detailed below:

Table 4
Statistical analysis of model evaluation results.

Algorithms	Mean	SD	Min	Max	*p* values (*t*-test)
LR	0.695	0.029	0.594	0.782	0.000
DT	0.833	0.021	0.758	0.889	0.000
SVM	0.840	0.024	0.770	0.906	0.000
RF	0.946	0.015	0.902	0.984	0.000
GBDT	**0.950**	**0.015**	**0.893**	**0.985**	——
XGBoost	0.938	0.016	0.890	0.979	0.000
MLP	0.716	0.034	0.490	0.820	0.000
LightGBM	0.939	0.016	0.883	0.981	0.000

(1) LDA-GBDT: This approach utilizes the LDA topic model to derive features from project descriptions, specifically focusing on the topic distribution. Subsequently, it employs GBDT for forecasting the fundraising performance of environmental crowdfunding projects. This model excels by elucidating the underlying themes in project descriptions, which can serve as indicators of alignment with potential backers' interests.
(2) TFIDF-GBDT: This method extracts TF-IDF values for words or phrases occurring more than 30 times (3691 instances) in project descriptions, utilizing them as predictive features. GBDT is then deployed for predicting fundraising performance. TF-IDF quantifies the significance of terms relative to a corpus. TFIDF-GBDT proves effective by pinpointing specific terms strongly associated with successful environmental crowdfunding projects.
(3) Doc2Vec-GBDT: In this approach, the Doc2Vec algorithm transforms project descriptions into 100-dimensional document vectors, serving as predictive features for GBDT. This representation preserves semantic information and enables the model to capture nuanced contextual relationships. Doc2Vec-GBDT excels by capturing text semantics and context, enhancing the algorithm's understanding of project descriptions and leading to more precise predictions of fundraising performance.
(4) LIWC-GBDT: This method computes the frequency of 98 LIWC terms in project descriptions to create predictive features. Subsequently, GBDT is applied to forecast the fundraising performance of environmental crowdfunding projects. LIWC, an analytical tool, quantifies word frequencies related to various linguistic and psychological categories (e.g., emotion, cognition). This model is effective by encapsulating linguistic and emotional aspects within project descriptions, serving as indicators of a project's appeal to potential backers.

To ensure a fair and rigorous comparison, we implemented these methods on the same dataset and within the same experimental environment. The performance of these methods is presented in Table 5. Among the four baseline models, LDA-GBDT exhibited the highest performance, achieving an AUC of 0.828. However, it still lags behind our proposed framework's performance by 5.9%. These results unequivocally underscore the superiority of our proposed framework when contrasted with state-of-the-art methods.

To ensure the reliability of the model comparison results, we performed 50 iterations of stratified 10-fold cross-validation on the entire dataset to obtain the performance scores (AUC) distributions for the four baseline models, as shown in Table 6. The statistical analysis results still support the aforementioned conclusions. This indicates that the proposed framework can accurately predict the fundraising performance of environmental crowdfunding projects, providing an effective method for pre-evaluating project fundraising capabilities.

4.4. Model interpretation

4.4.1. Feature importance evaluation

SHAP values have been utilized to assess the relative importance of different features in predicting the fundraising performance of environmental crowdfunding projects, as depicted in Fig. 3. A wider distribution range of SHAP values for a feature indicates higher relative importance. Based on the SHAP plot, two key conclusions have been drawn:

(1) The most critical feature of the model is the fundraising goal. This finding is consistent with previous research on the prediction of general crowdfunding projects' fundraising performance (Al-Qershi et al., 2022; Guo et al., 2020).
(2) Overall, the structural features and agency features of the projects (e.g., fundraising goal, organization age, and project duration) hold significantly greater importance than most content features (e.g., text length, text complexity, and text logicality). This observation aligns with established theoretical knowledge: as crowdfunding projects present donors with complexity, donors often rely on simple information cues rather than detailed content reasoning to make their decisions (Zhu, Huang, & Liu, 2023).

These two findings affirm that SHAP values provide effective and theoretically expected evaluations of feature importance.

4.4.2. Feature effect visualization

ALE plots have been employed to visualize the correlation between feature values and the fundraising performance of environmental crowdfunding projects. This study specifically focuses on the analysis of six pivotal features: fundraising goal, organization age, project duration, text complexity, text length, and text positivity. Fig. 4 displays the ALE plots for these features, from which six key insights have emerged:

Table 5
Results of comparison with state-of-the-art methods.

Methods	Accuracy	Recall	Precision	F1 score	AUC
TFIDF-GBDT	0.739	0.718	0.738	0.723	0.718
LIWC-GBDT	0.740	0.726	0.735	0.729	0.726
Doc2Vec-GBDT	0.752	0.733	0.751	0.738	0.733
LDA-GBDT	0.839	0.828	0.838	0.832	0.828
Proposed framework	**0.899**	**0.887**	**0.905**	**0.894**	**0.887**

Table 6
Statistical analysis of model comparison results.

Classifiers	Mean	SD	Min	Max	*p* values (*t*-test)
TFIDF-GBDT	0.820	0.023	0.753	0.892	0.000
Doc2Vec-GBDT	0.851	0.022	0.778	0.909	0.000
LIWC-GBDT	0.862	0.021	0.785	0.924	0.000
LDA-GBDT	0.916	0.019	0.864	0.970	0.000
Proposed framework	0.950	0.015	0.893	0.985	——

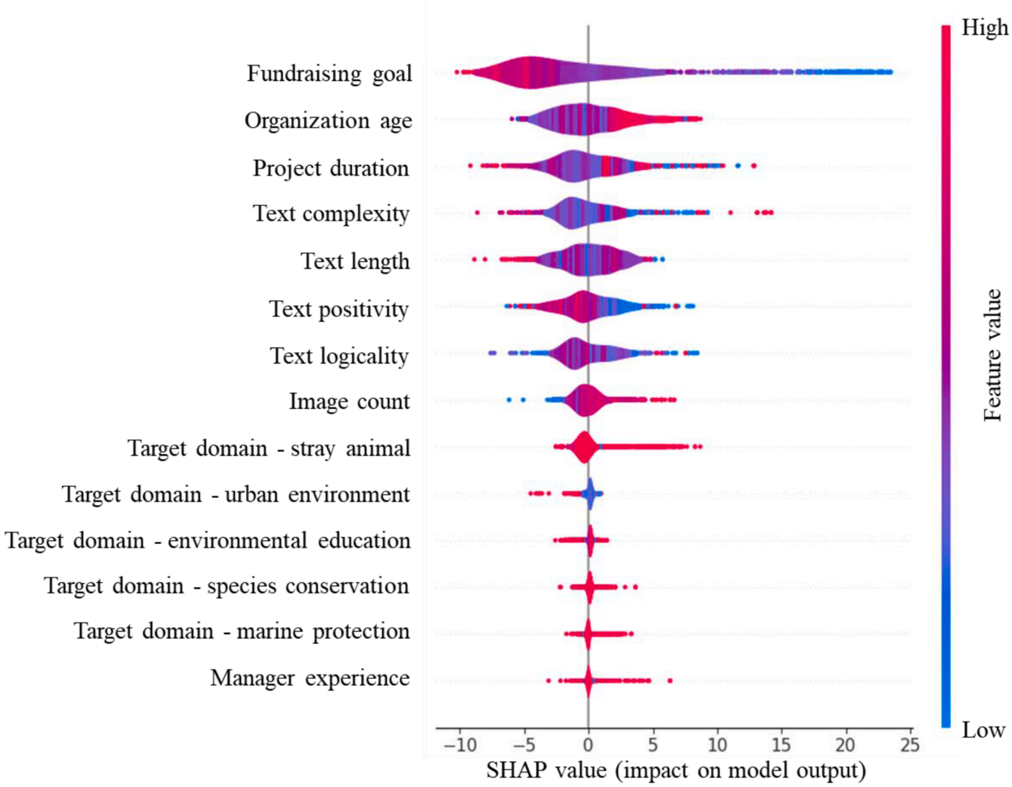

Fig. 3. SHAP summary plots of the predictive model.

(1) The ALE curve for the fundraising goal demonstrates an overall undulating descending pattern, indicating an inverse relationship between the fundraising goal and the fundraising performance of environmental crowdfunding projects. This observation corroborates prior research findings, which suggest that a higher fundraising goal can diminish the perceived feasibility of projects and heighten perceived risks, consequently reducing a project's fundraising performance (Koch & Siering, 2019; Lagazio & Querci, 2018; Zhang et al., 2023).
(2) The ALE curve for organization age exhibits a U-shaped trajectory, signifying a non-linear connection between organization age and the fundraising performance of environmental crowdfunding projects. This result accounts for the intricate impact of organization age documented in extant studies: Young organizations, with their upward potential, positively influence crowdfunding project fundraising performance, while mature organizations, with their wealth of experience, also bolster fundraising performance (Prokop & Wang, 2022; Ralcheva & Roosenboom, 2020).
(3) The ALE curve for project duration displays a U-shaped pattern, indicating a non-linear link between project duration and the fundraising performance of environmental crowdfunding projects. This result is consistent with the theory that, while providing more time for potential donors to explore project features, long project durations may also convey a lack of urgency or confidence on the part of the project creator (Ba et al., 2020; Chen et al., 2023; Lagazio & Querci, 2018; Mollick, 2014).
(4) The ALE curve for text complexity showcases an inverted U-shaped pattern, suggesting a non-linear link between text complexity and the fundraising performance of environmental crowdfunding projects. This finding aligns with existing literature on the effects of text complexity: To a certain extent, enhancing text complexity can amplify the quality signal of the project, positively impacting crowdfunding project fundraising performance. However, excessive text complexity hampers

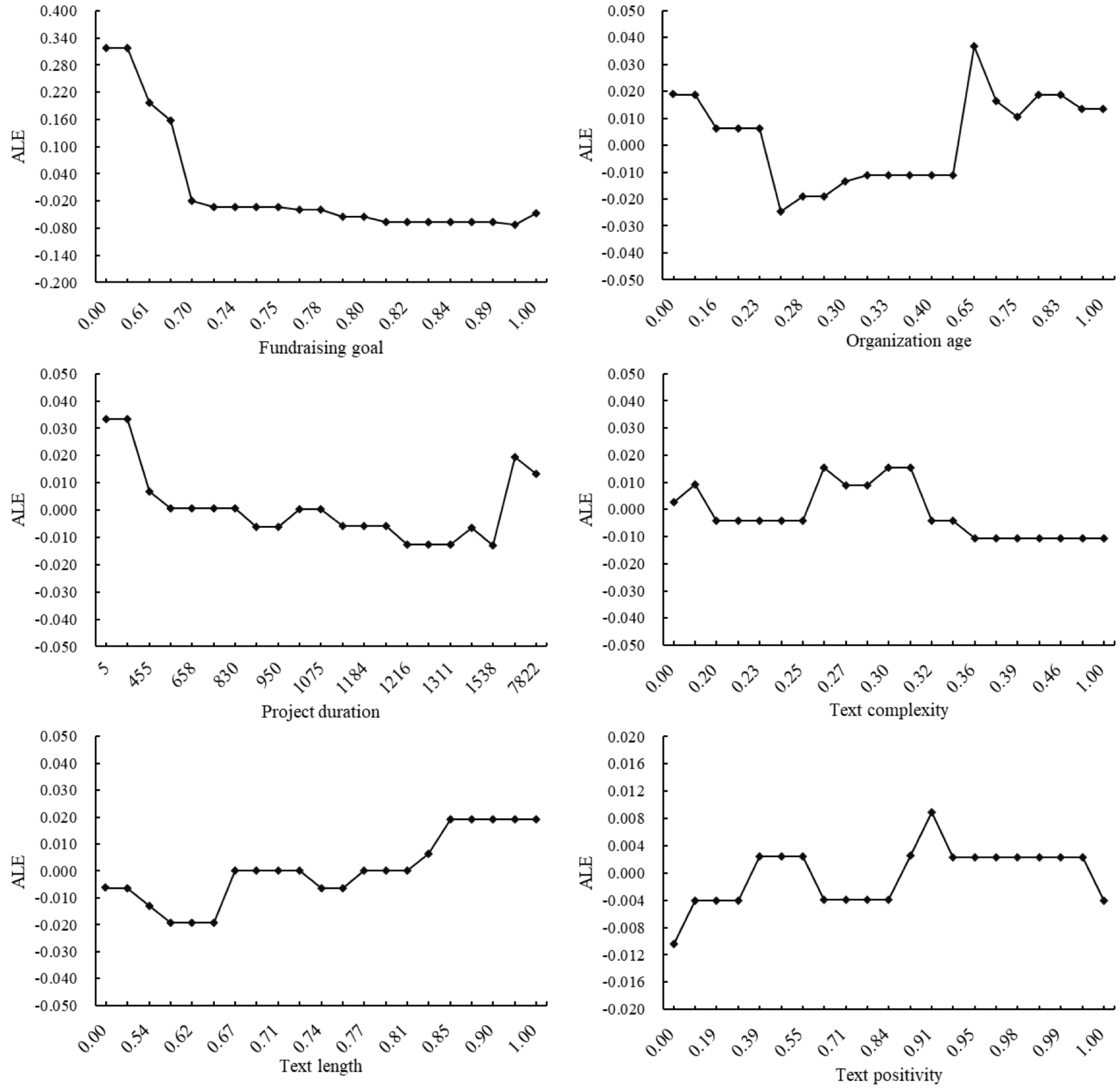

Fig. 4. ALE plots of six important features.

potential donors' comprehension of the project, negatively affecting fundraising performance (Li et al., 2023; Markowitz & Shulman, 2021).

(5) The ALE curve for text length displays an overall fluctuating rising trend, indicating a positive association between project description length and the fundraising performance of environmental crowdfunding projects. This observation further supports prevailing perspectives, indicating that longer project descriptions facilitate donors' better understanding of project goals and enhance perceived quality, thereby improving a project's fundraising performance (Chen et al., 2023; Zhang et al., 2022).

(6) The ALE curve for text positivity demonstrates an inverted U-shaped pattern, suggesting a non-linear link between text positivity and the fundraising performance of environmental crowdfunding projects. These results align with the findings of Zhou et al. (2018), which suggest that a moderate positive tone in project descriptions can help boost donations from potential donors, but excessive positive tone may be inappropriate.

These findings underscore the accuracy of ALE plots in depicting the relationship between predictive features and the fundraising performance of environmental crowdfunding projects. These insights can be harnessed to enhance the design of environmental crowdfunding projects.

5. Implications

5.1. Theoretical implications

As far as we are aware, this study represents the first attempt to integrate interpretable machine learning techniques for predicting the fundraising performance of environmental crowdfunding projects, thus complementing the existing literature on crowdfunding project fundraising prediction.

The first contribution of this study lies in its expansion of domain-specific crowdfunding project fundraising prediction research by pioneering the exploration of fundraising performance prediction within the context of environmental crowdfunding. While previous research has predominantly focused on general crowdfunding projects (Du et al., 2021; Wang, He, Jim, & Goh, 2021), with some limited investigations in specific domains like technology and gaming (Faralli, Rittinghaus, Samsami, Distante, & Unitelma, 2021; Huang, Pickernell, Battisti, & Nguyen, 2022; Song et al., 2019; Tang et al., 2023), there has been a notable gap in research addressing environmental crowdfunding projects. This study fills this gap and extends the boundaries of crowdfunding research by specifically examining the prediction of fundraising performance in the environmental crowdfunding sector, thereby broadening the understanding of crowdfunding project fundraising prediction within this particular domain.

The second significant contribution of this study pertains to the development of a more theoretically grounded feature set for predicting crowdfunding project fundraising performance. In contrast to previous research that often employed text vectors without strong theoretical foundations, such as LDA, TF-IDF, and Doc2Vec (Chen & Shen, 2019; Kaminski & Hopp, 2020; Tang et al., 2023; Yuan et al., 2016), this study takes a different approach. The features used in constructing the predictive model are thoughtfully selected based on explanatory research, ensuring a stronger theoretical underpinning. Consequently, this feature set exhibits superior predictive performance, highlighting the potential for inspiring future research in the domain of crowdfunding project fundraising performance prediction.

The third major contribution of this study is the novel approach it introduces to enhance the interpretability of crowdfunding project fundraising performance prediction models. While previous research has primarily focused on developing complex models to improve the prediction accuracy of crowdfunding project fundraising performance (e.g., Babayoff & Shehory, 2022; Tang et al., 2023; Yeh & Chen, 2020), this study stands out as the first to emphasize the importance of interpretability. By employing post-interpretation techniques, specifically SHAP values and ALE plots, this study provides a groundbreaking method to enhance the transparency and comprehensibility of crowdfunding project fundraising prediction models. This approach not only increases the reliability of the models but also enriches the theoretical understanding of the relationships among variables within the model, contributing to a deeper insight into the underlying mechanisms at play.

5.2. Practical implications

The framework presented in this study also holds significant practical implications for stakeholders in environmental crowdfunding.

First and foremost, environmental crowdfunding project creators have the opportunity to enhance their project designs based on the findings of this study, thereby improving the performance of fundraising efforts. Our research has unveiled intricate, non-linear relationships between project attributes and the fundraising outcomes of environmental crowdfunding projects. These insights serve as a direct guide for project creators, enabling them to optimize project design effectively. For example, they can achieve this by setting a relatively small fundraising goal, choosing either an emerging or established institution to oversee the project, opting for a shorter duration, and crafting a project description of moderate complexity, ample length, and moderate positivity. Additionally, our proposed framework empowers environmental crowdfunding project creators to develop customized tools for preemptively assessing their project's fundraising potential. Creators can utilize the framework's features with historical project data to train predictive models for project fundraising performance. By inputting the details of upcoming projects into the model, creators can anticipate and proactively refine their project designs.

Furthermore, crowdfunding platform administrators can devise traffic allocation algorithms based on the proposed framework to enhance the overall fundraising performance of environmental crowdfunding projects hosted on their platform. For crowdfunding platforms, optimizing project fundraising performance is pivotal as it directly influences user retention and loyalty. Consequently, platform administrators must judiciously allocate platform resources among different projects to maximize collective fundraising success. Building on the proposed framework, platform administrators can formulate algorithms to classify projects as high or low performance during the early stages of fundraising, relying on project features. To elevate overall fundraising success, projects predicted to have low performance should receive greater exposure, such as more frequent featuring on the platform's homepage.

Lastly, local governments, as crucial players in environmental governance, can establish region-specific environmental crowdfunding project design criteria based on the framework's insights. Developing project design criteria is instrumental in enhancing the fundraising performance of environmental crowdfunding projects. However, it's important to acknowledge that these criteria must be adapted to the unique characteristics of each region, given that key predictors of fundraising success in environmental crowdfunding projects may vary. Local governments, especially those with authority over environmental organizations, such as in countries like China, can collect data on environmental crowdfunding projects to create regional predictive models for fundraising performance and identify significant features based on the proposed framework. Armed with these findings, local governments can craft project design criteria tailored to specific regions to assist environmental organizations in optimizing their crowdfunding efforts.

6. Conclusion

Crowdfunding has gradually become a vital means for environmental organizations to raise funds for environmental projects. However, the fundraising performance of environmental crowdfunding projects is not optimistic, and improving their fundraising performance is imperative. Achieving this goal requires two prerequisites: Firstly, accurately predicting the fundraising performance of each environmental crowdfunding project to identify projects that need improvement. Secondly, revealing the correlations between different features and the fundraising performance of environmental crowdfunding projects to understand how to improve project design. To address both of these issues, this study proposes an interpretable framework to predict the fundraising performance of environmental crowdfunding projects.

The framework utilizes ten theoretically meaningful features to construct the feature set for building the predictive model. Eight different algorithms are selected to train the predictive model, and two post-hoc interpretation techniques, SHAP values, and ALE plots, are employed to visualize the role of predictive features in predicting the fundraising performance of environmental crowdfunding projects. The framework is validated using the Tencent Charity environmental crowdfunding project dataset. The results demonstrate that the predictive performance of this framework surpasses current state-of-the-art methods by at least 5.9%. Moreover, the post-hoc interpretation techniques in the framework accurately depict the roles of the features.

However, this study has two limitations that need to be addressed in future research. Firstly, the proposed framework is only validated on the Tencent Charity crowdfunding project data, and its performance on other datasets requires further examination. Future research can obtain datasets from multiple sources to enhance the credibility of the framework. Secondly, in terms of post-hoc interpretation of predictive models, this study only explores how to visualize the main effects of features. Interactions between features were not systematically explored. Future research can attempt to incorporate the exploration of interaction effects into the framework, enabling researchers and practitioners to use the framework to identify significant interaction effects.

CRediT authorship contribution statement

Zhanyu Liu: Writing – original draft, Writing – review & editing, Methodology, Software. **Saiquan Hu:** Conceptualization, Writing – review & editing, Supervision, Funding acquisition.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ipm.2023.103587.

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