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How much do social connections matter in fundraising outcomes?

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Abstract

This study examines the role of social connections and network centrality in attracting funders to crowdfunding campaigns. We classify social connections as either external (e.g., Facebook) or internal (e.g., investing in online platforms through resource exchange). Drawing from the 108,463 crowdfunding campaigns on the online platform Kickstarter from April 21, 2009, to July 24, 2019, we apply external linkages and online followers to estimate the effect of external social connections. We construct a digraph network for the internal social connections and use PageRank, HITS, and centrality to obtain the weights of the nodes. Next, we compare the performance change of several prediction algorithms by feeding social connection-related variables. This study has several findings. First, for external social connections, having more online followers improves the funding success rate of a campaign. Second, for internal social connections, only authority and degree in centrality positively affect the number of funders and the campaign's financing progress among the weights of the nodes. Third, using social connection variables improves the prediction algorithms for funding outcomes. Fourth, external social connections exert greater funding outcomes than internal social connections. Fourth, entrepreneurs should extend their external social connections to their internal social connections, and network centrality expedites project financing. Fifth, the effect of social connections on fundraising outcomes varies among the campaign categories. Fundraisers who are online influencers should leverage their online social connections, notably for the project categories that matter.

Keywords: Crowdfunding, Social connections, Social networks, Kickstarter, Fundraising, Online influence

Introduction

Network theory posits that a node with more edges—network centrality—exerts a greater influence. Likewise, online financing is affected by fundraisers' influence (Ciro and Mario 2021; Wang et al. 2020). A fundraiser who is a key opinion leader (KOL) or an online influencer may elicit greater support and response from online followers (Cookson and Niessner 2020). Fundraisers can use online community platforms such as Facebook to link up with potential external investors to promote their creative ideas, advertise their campaigns, and raise funds for their projects. Simultaneously, the social ties formed on online platforms such as Kickstarter can improve the fundraising outcome (Rawhouser et al. 2019). External and internal forms of social connections are a

conduit for expanding the influence of entrepreneurs (Davies 2015). However, research on crowdfunding campaigns has rarely investigated network centrality and the underexplored relative roles of internal and external social connections.

Some investors may support online campaigns because of their online social relationships formed externally with the fundraisers, often measured by the number of followers (Memon et al. 2020). Thus, external social connections provide a habitual form of communication and promotion (Yu et al. 2020), enlarging the funding catchment pool and ensuring a higher chance of funding success (Sahasranamam and Nandakumar 2020). Furthermore, as social interaction involves peer communication fostering online influence, the more online followers a fundraiser has, the greater is the latter's social influence (Lehner 2013). Network analysis indicates that the weight of the node linked to more nodes will be greater (KOL or key online influencer) (de Souza et al. 2020).

While many studies highlight the value of external social connections, research on internal social connections and network centrality is scant. The online financing platform can be viewed as a social community where numerous investors and fundraisers interact and communicate on matters such as investing. Such behavior can be regarded as the connection between the nodes, thus creating an internal network structure (Herrera et al. 2020). We can evaluate the KOL by obtaining the weights of the nodes, such as network centrality (Cerqueti et al. 2020). Nevertheless, we do not know how the internal social connections affect the fundraising outcomes, nor can we weigh the importance of internal and external social connections, making it challenging to guide crowdfunding strategies.

Thus, we believe that research opportunities exist. First, most studies do not distinguish and compare the impact of internal and external social connections. Online financing may be affected by both connections, but the clarity or the extent of their influence and their comparative advantages are unclear. Second, the differences in social connections among the project categories are less understood. Third, the extent to which internal and external social connections improve the prediction of fundraising outcomes is also relatively understudied. Therefore, knowledge regarding the weights of internal and external social connections can guide online entrepreneurs effectively.

This study poses several research questions to analyze how social connections influence fundraising outcomes. First, how do external and internal social connections affect fundraising outcomes—how do followers and weights of the nodes (e.g., PageRank, centrality) affect fundraising outcomes? Second, if social connections can influence pledge results, will using machine learning on social connections improve the predictive power of the fundraising outcome for online projects? Third, is there a difference between the internal and external social connections in the prediction model? Which is more predictive, and does the predictive power depend on the project category? Our study draws data from the online platform, Kickstarter, having a large pool of small start-ups seeking funding under several project categories to address the above questions. A suite of machine learning algorithms is employed to predict the fundraising performance and then compared to validate the reliability and predictive power of social connections. Further, a cross-category comparison was conducted to understand the extent of the influence of social connections on crowdfunding entrepreneurship. Theoretically, these analyses help detect the degree of internal and external social connections. Practically,

they can guide entrepreneurs on how to position their crowdfunding campaigns appropriately.

The remainder of this paper is organized as follows. Section 2 presents a literature review, and Sect. 3 describes the study's methodology. Further, Sect. 4 lists and discusses the results. Finally, Sect. 5 concludes the paper.

Literature review

Factors affecting fundraising outcomes

Many factors influence online investment decisions (Atmaca and Karadaş 2020; de Crescenzo et al. 2020). Studies suggest that relatives are the main sources of funding support at the early stage of crowdfunding (Groza et al. 2020). Another aspect is the group behavior of the fund backers—the herd or hive mindset (Zhang and Liu 2012). Investors follow the crowd, believing in safety in numbers (Li et al. 2020a, b). Late-stage fund backers judge the quality of a project by adopting the herd effect of early backers as a proxy for quality.

As many factors affect the outcomes of the crowdfunding projects, various features such as funding goal, duration, cultural customs, and location proximity should be considered when analyzing funding outcomes (Yuan et al. 2016, 2021; Zha et al. 2020). Additionally, feature engineering is a vital pre-step (Kim et al. 2020). Crowdfunding projects are generally displayed through text, images, and videos. Thus, textual, visual, and linguistic signals can influence funding outcomes (Kaminski and Hopp 2019).

According to Mollick (2014), the most important antecedent of online financing is the quality of a crowdfunding project. Many studies have reported that an acceptable format, high readability, and an elaborate multimedia display are high-quality signals (Kang et al. 2016). Another aspect is the influence of the fundraiser, usually typified as the entrepreneur's reputation, education, social status, and experience (Bernardino and Santos 2016). Many studies posit that seasoned investors are adept at identifying the quality of crowdfunding projects (Bi et al. 2017).

While crowdfunding projects are prevalent, differences exist among the project categories (Wang et al. 2021). In some categories, fund backers focus on project creativity; in others, it is the fundraiser's attributes (Calic and Shevchenko 2020). In many cases, established fundraisers leading a campaign are better at attracting funding, although their role in social connections is inconclusive. Further, geographical distance, social capital, and interaction may influence crowdfunding (Giudici et al. 2018; Kang et al. 2017).

Feature selection strongly influences interpretation and prediction (Uthayakumar et al. 2020). This leads to differences in funding success rates as not all categories yield the same fundraising outcomes. For example, in Kickstarter, the success rate of art-related projects is significantly higher than that of technology-related projects (Wang et al. 2017a, b). Art-related projects rely on social connections to reach out and self-promote. Thus, celebrity artists can always overcome geographical constraints and influence a broader market (Guo et al. 2018), highlighting the influence of node weights. The identity and background of the entrepreneurs can also influence the results. Social and commercial entrepreneurs present noticeable differences in funding outcomes (Parhan-kangas and Renko 2017).

In addition to feature selection, the choice of algorithm can affect the prediction performance of funding success. For example, some studies have suggested that the deep learning method (multilayer neural network) yields better results (Wang et al. 2020a, b; Zhang 2020). Others have shown that support vector machine (SVM) and logistic regression (LR) have strong predictive power (Turiel and Aste 2020). However, these algorithms generally do not include entrepreneurs' social connections.

Influence of social connections on funding outcomes

Among the factors that influence crowdfunding projects (Moritz and Block 2016), social factors are drivers that scholars heed (Lukkarinen, Teich, Wallenius, and Wallenius, 2016). Fundraisers are embedded in the online network as nodes, providing both opportunities and constraints. According to network theory, the more edges directed to a node—network centrality—the greater is the influence of that node (Li et al. 2020). Social capital is a channel to promote product innovation (Eiteneyer et al. 2019). It enhances the attractiveness of a project and precedes crowdfunding success (Gleasure and Morgan 2018). However, the influence of social capital on equity crowdfunding performance is multifaceted (Troise et al. 2020). In crowdfunding, the social capital accumulated by fundraisers is critical. It can affect the success of a crowdfunding project (Jain and Sinha 2019). The disadvantage of relying on social connections on social media is the information value (Jeske and Shultz 2016).

Following the work of Granovetter (1973), scholars have extensively studied the use of social networks and their influence (Lin et al. 2020). For example, crowdfunding projects receive monetary support from online followers. Thus, a project having more online followers would imply a higher chance of receiving pledge money (Clauss et al. 2020). Therefore, the funding success rate is correlated with the pool of online followers. In short, the online influence of the fundraiser, especially KOL, can attract fund backers. Thus, social network ties have different roles in attracting backers to crowdfunded campaigns (Foster 2019), explaining the effect of network centrality. Moreover, innovation and social capital have an interactive effect on the willingness to participate in crowdfunding (Medina-Molina et al. 2019).

Additionally, there is a diametric view to social connections, not conducive to online funding. For some backers, the quality of a crowdfunding project is the primary investment evaluation yardstick (da Cruz 2018), and online social connections are not always correlated with the quality of a project. Although the information received by the fund backers may be rich, their attitude toward any information from the online advertisements and promotions may not be in the same measure (LaRose et al. 2014; Palos-Sanchez et al. 2019). Therefore, some fund backers may be deterred by any promotional platform mounted through social media. Further, many fundraisers have friends, relatives, or colleagues as backers, notably at the early stages of funding (Liang et al. 2019). Online connections may not sway such backers.

In addition to social media connections based on the social exchange theory, some studies have focused on the connections formed by resource exchange (Zhao et al. 2017). In the virtual community of online crowdfunding, investors fund a project to form a resource exchange and connection relationship. Therefore, project launchers well

backed in other projects are more likely to obtain funding (Colombo et al. 2015; Skirnevskiy et al. 2017).

Mechanism of network centrality on investors

Social capital and social connections are related but different concepts; some studies have tried to distinguish the impact of the two (Ellison et al. 2011). Social capital is the network of relationships among the users living and working in a particular society, enabling effective functioning (Coleman 1988; Rey-Garcia and Mato-Santiso 2020); social connections are the experience of feeling close and connected to others. Furthermore, it involves feeling loved, cared for, and valued and forms the basis of interpersonal relationships (Eisenberger and Cole 2012). Therefore, social connections can be perceived as a part of social capital.

One reason the crowdfunding project fails is that the campaign is not shared with potential fund backers. Therefore, tapping on the social connections of fundraisers and using online recommendations for crowdfunding projects heighten the success rate. Zheng et al. (2014) reported that combining the topics posted on Twitter with a project's features can increase the accuracy of personalized recommendations to 84%. Additionally, potential investors can use social media to evaluate campaigns and share opinions quickly (Chen et al. 2020). Thus, social media enable crowdfunding projects to communicate better and attract more fund backers (Ibrahim 2012). Additionally, physical distance and timing can influence crowdfunding investment intention (Agrawal et al. 2015).

Owing to the external effects and information asymmetry, the mechanism of crowdfunding platforms is generally detected using the signaling theory (Belleflamme et al. 2015). Some studies distinguish social capital and highlight the value of internal capital for early contributions (Colombo et al. 2015). The rationale for the mechanism of network centrality is as follows: (1) it extends the personal influence of the crowdfunder, and (2) it provides an adequate signal quality (Stuart and Sorenson 2007). One reason for this mechanism exerting a role lies in the impact of reciprocity produced by resource exchange (Zvilichovsky et al. 2015). Studies posit that psychological compensation and utility maximization justify reciprocity in behavior (Vismara 2016). Additionally, social connections can predict loan defaults, indicating that the project risk can be detected earlier (Everett 2015). Information heterogeneity and crowdfunders' social network promote the attractiveness of a project and hence funding success (Polzin et al. 2018).

Methodology

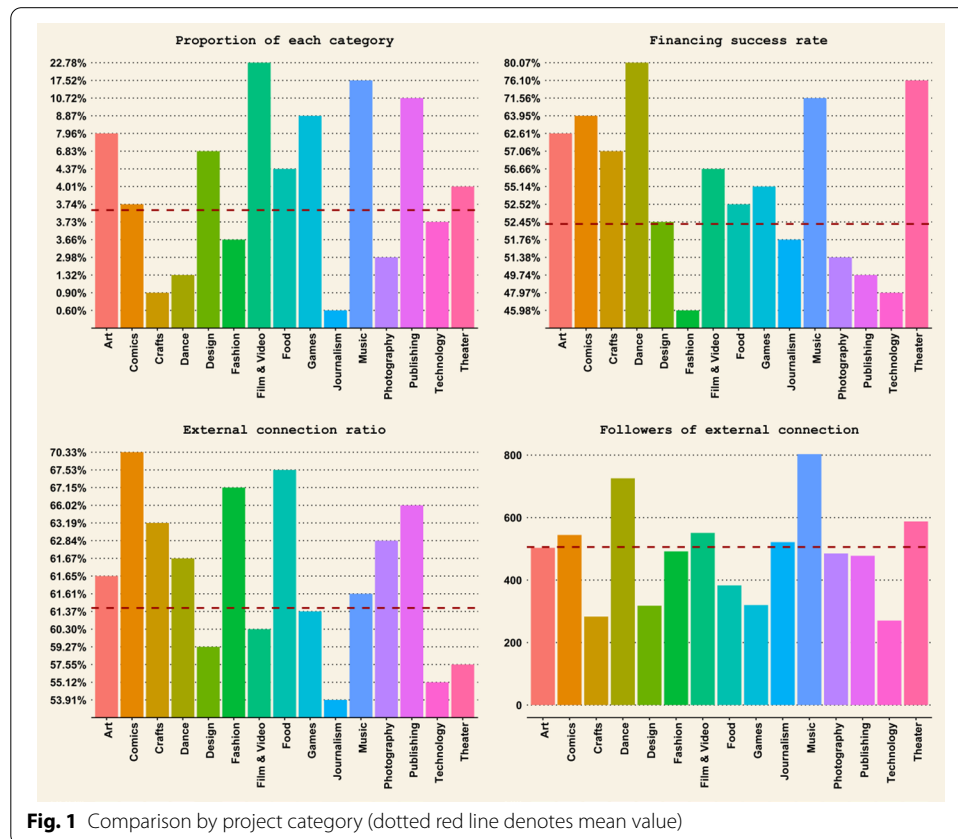
Research data

We employed Python to build a crawler to trawl the campaigns on Kickstarter. The observation window was from April 21, 2009, to July 24, 2019. All raw data were stored in MySQL, comprising 108,463 public campaigns, as shown in Table 1. Among the categories, the funding goal of "Technology" is the highest (\$53,906.90), while "Crafts" is the lowest (\$4476.06), with an order of magnitude difference. The success rate of crowdfunding projects is 58.86%, although this measure varies by project category.

Figure 1 profiles the 15 project categories residing on Kickstarter. By proportion, the category Film and Video is the largest (22.78%), while Journalism is the smallest (0.6%). Dance has the best funding success rate (80.07%), while Fashion has the worst (45.98%).

Table 1 Sample statistics of crowdfunding project categories on Kickstarter

Category	No. of projects	Percentage (%)	Goal (\$)	Pledge amount (\$)	Funding duration (days)	Funding success (%)	External connections (%)	No. of online followers
Art	8637	7.96	19,532.67	4348.41	33.02	62.61	61.65	503
Comics	4055	3.74	8058.28	10,124.01	35.85	63.95	70.33	544
Crafts	978	0.90	4476.06	3573.21	30.30	57.06	63.19	283
Dance	1435	1.32	4624.93	4003.78	32.82	80.07	61.67	726
Design	7403	6.83	23,578.59	33,767.12	34.76	52.45	59.27	318
Fashion	3967	3.66	11,717.49	10,573.54	32.80	45.98	67.15	492
Film & Video	24,708	22.78	25,838.10	9697.94	35.67	56.66	60.30	551
Food	4743	4.37	16,220.68	10,100.16	33.85	52.52	67.53	383
Games	9620	8.87	31,313.80	37,066.99	33.41	55.14	61.37	320
Journalism	653	0.60	12,532.24	6362.10	36.92	51.76	53.91	522
Music	19,005	17.52	8000.35	5252.60	35.71	71.56	61.61	803
Photography	3235	2.98	7490.50	4438.80	35.06	51.38	62.84	485
Publishing	11,629	10.72	8561.05	5039.99	34.44	49.74	66.02	478
Technology	4044	3.73	53,906.90	49,445.84	34.97	47.97	55.12	271
Theater	4351	4.01	8947.40	4919.98	33.97	76.10	57.55	588
Sum	108,463		18,356.11	13,112.26	34.70	58.86	62.00	526



External social connections are the weakest for Journalism fundraisers (53.91%) and highest for Comics (70.33%). This suggests that the fundraisers of Journalism projects tend to rely less on external social connections. For fundraisers linked to the external social connections, the most significant number of online followers is found in Music (803) and the least in Technology (471).

Research method

Fundraisers connect through their external social networks (e.g., Facebook) or form internal social connections through dedicated online financing platforms using resource exchange (e.g., Kickstarter) in an open network environment. Some studies have distinguished the effects of these two forms of social connections (Han and Hovav 2013). Online users form various connections. External connections connect the distal to the proximal to expand the social capital for the online user and achieve external social adaptability and personal development (Costanzo 1992). Therefore, external connections on an external platform are outward-oriented resources. Conversely, internal connections are those formed within the system through resource exchange within a specific range. For example, the interaction for most users on an online platform can be regarded as an internal connection (Bristow and Mowen 1998). There are many forms of resource exchange in internal connections, including social activity, personal interaction, locus of control, sensation-seeking, innovativeness, and affinity. Furthermore, different forms of resource exchange have different effects on users (Haridakis and Hanson 2009). Thus, on the crowdfunding platform, resource exchange can be regarded as internal connections. Figure 2 highlights the classification of social connections and their measures.

Moreover, lurking exists in social connections; some nodes in a community may be more inclined to reveal a behavior or pattern that should belong to another community (Chaboud 2019). In short, saying one thing and doing another is a shortcoming in social analysis (Liu et al. 2020). Lurking can arise due to occupation, gender, or social norms (Park et al. 2012). Therefore, we divided the social connections into internal and external social connections to weaken the influence of the lurking to some extent. We used Facebook, Twitter, YouTube, Myspace, Flickr, and LinkedIn to measure the virtual groups for external social connections. As lurkers easily influence external social connections, we turned to internal social connections to mitigate this influence. We used the user’s behavior (resource exchange) to build the connections for the internal social

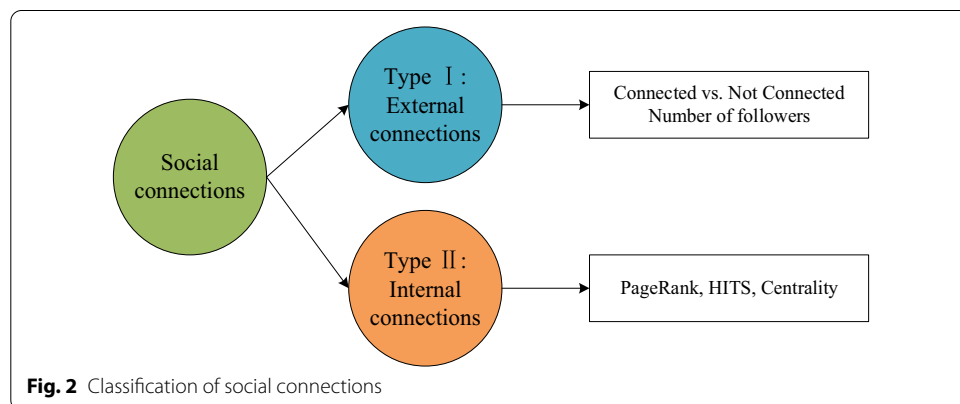


Fig. 2 Classification of social connections

connections, rather than the “following” or “followers” groups. Thus, it allowed us to observe the actual investing behavior and resource exchange, dampening the influence of the lurking users.

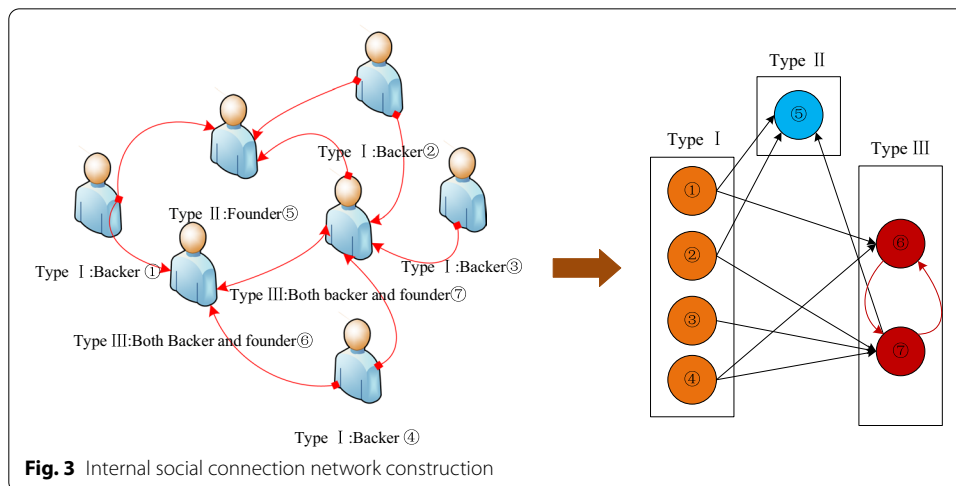
Next, we built a network analysis model for internal social connections (see Fig. 3). Specifically, we categorized the participants of the crowdfunding projects into the following: (I) Backer, only investing in but not launching a project; (II) Founder, only launches a crowdfunding project and does not invest in it; and (III) Backer and founder, a fundraiser and investor. Using this classification, we built a directed network and obtained the PageRank, Authority, Hub, Degree, and Eigenvector of the nodes using the *NetworkX* package in Python ver. 3.9.6.

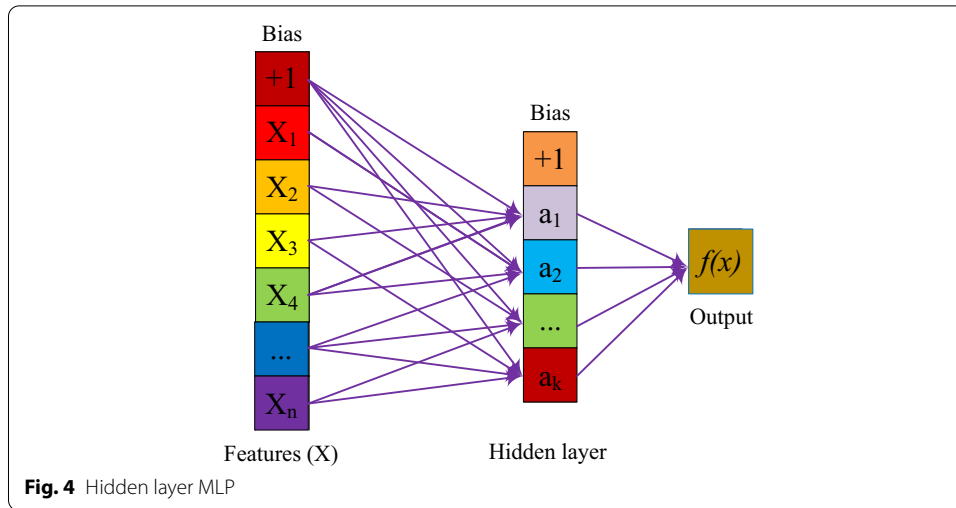
To predict the impact of social connections on crowdfunding project financing, we applied eight common machine learning algorithms for comparison (Chen et al. 2012; Wang, Tan, and Wang, 2017). They are deep learning, decision tree, LR, random forest, Bayesian inference, K-nearest neighbor (KNN), AdaBoost, and SVM. The deep learning algorithm uses a multilayer perceptron (MLP), a supervised learning algorithm that learns a function $f(x)$ by training on a dataset. It can learn a nonlinear function approximator for classification. Deep learning differs from LR, as one or more nonlinear layers exist between the input and output layers. These were labeled hidden layers (see Fig. 4).

As the financing results of the crowdfunding projects are expressed as binary variables, we use the sigmoid function as the activation function, and the form is shown in Eq. (1). The output of the sigmoid function was set between 0 and 1.

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{1}$$

A decision tree is a structure that includes a root node, branches, and leaf nodes. Each internal node denotes a test on an attribute, each branch denotes the outcome of a test, and each leaf node holds a class label. The topmost node in the tree is the root node. Information gain is applied as a splitting criterion for constructing the decision tree, as shown in Eq. (2). Thus, the most significant information gain among the remaining variables is always preferred when constructing the decision tree.





$$H(S) = -\frac{p}{p+n} \log_2\left(\frac{p}{p+n}\right) - \frac{n}{p+n} \log_2\left(\frac{n}{p+n}\right) \tag{2}$$

Random forest is an ensemble learning method; it is a classification algorithm comprising numerous individual decision trees that operate as an ensemble. Each decision tree in the random forest spits out a class prediction, and the class with the most votes becomes the model's prediction. Random sampling and split nodes are the two most important steps in building a random forest. Random forests have many advantages, such as resistance to overfitting.

LR assumes that the dependent variable y obeys a Bernoulli distribution and uses a logistic function to model a binary dependent variable. LR introduces nonlinear factors through a sigmoid function to handle the problem of binary classification. The LR form is usually expressed as in Eq. (3), where x is the input, θ is the parameter to be estimated, and $g(x)$ is the sigmoid function. The goal is to model the probability of the dependent variable being 0 or 1 based on the experimental data.

$$h_{\theta}(x) = g\left(\theta^T x\right) = \Pr(y = 1|x; \theta), g(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

KNN, as shown in Eq. (4), measures the distance to the nearest K instances and lets the instances vote. K is typically chosen to be odd-valued. As the KNN algorithm is sensitive to the units of measurement, it is necessary to normalize the feature values when building the model.

$$D(Q, C) \equiv \sqrt{\sum_{i=1}^n (q_i - c_i)^2} \tag{4}$$

AdaBoost is a common prediction algorithm for boosting learning and data classification by adaptively adjusting suitable weights. AdaBoost divides classifiers into weak and strong classifiers. Through training, the sample weights incorrectly classified by the previous round of the weak classifier are improved, and those classified correctly are reduced.

The weighted majority voting method was used to classify the samples. Equation (5) shows the classifier, where $G_m(x)$ is the trained classifier, and α_i is the weight for $G_i(x)$.

$$G_m(x) = \text{sign}(f(x)) = \text{sign}\left(\sum_{i=1}^M \alpha_i G_i(x)\right) \tag{5}$$

SVM is a discriminant method that combines computational learning theory, known methods in linear discriminant functions, and optimization theory. SVM finds a hyperplane $g(x) = w^t x + w_0 = 0$. The two categories in a dataset can be separated by transforming the data into a higher-dimensional space using a kernel function (Suykens and Vandewalle 1999). Thus, the distance from x to the hyperplane is denoted as $(w^t x - w_0) / \|w\|$ or $g(x) / \|w\|$.

Table 2 presents the key features of the algorithms used in this paper.

Empirical models

Given the characteristics of crowdfunding, there are many ways to measure the impact of social connections, including (1) whether the planned financing goal has been achieved, (2) the overall financing progress of the project, and (3) the number of fund backers. The dependent variable of the econometric model can assume one of the three forms, yielding three models in estimating the impact of social connections on funding outcomes. The structure of the three econometric models obeys Eq. (6), where S'_i is the set of variables for the internal and external social connections of project i , and C'_i denotes the vector of the control variables. Next, α is the intercept, and β and γ are the coefficients for the social connections and the control variables, respectively; ε_i are the random disturbance factors, assumed to be normally distributed with $\varepsilon \sim N(0, \delta^2)$. F_i denotes the dependent variable used for project i .

$$F_i = \alpha + S'_i \cdot \beta + C'_i \cdot \gamma + \varepsilon_i \tag{6}$$

Table 2 Key features of algorithms used

MLP	Decision tree	LR	Random forest
Feed data to input layer	Compute information gain for each variable	Construct prediction function, using Eq. (3)	Random sampling Split nodes
Set connection factor w , offset b in hidden layer	Select the variable with largest information gain as the root node	Construct loss function $J(\theta)$	Repeat step 2 until no more splits
Use Sigmoid function as activation function	Repeat above steps until tree is built	Using gradient descent to find smallest $J(\theta)$	Repeat steps 1 to 3 to build decision trees to form a random forest
Output classification results	KNN	AdaBoost	SVM
Bayesian inference	Randomly select n nodes as classification centres	Initialize weight distribution D_1	Find number of classifiers
Set a priori probability	Compute distance from each node to the centres	Train weak classifier	Apply kernel function
Set conditional probability from the given information	Update centres	Combine the trained weak classifiers into a strong classifier	Train data to obtain hyperplane
Transform a priori probability into posterior probability with the information	Repeat steps 1 to 3 until convergence		Repeat steps 1 to 3 until convergence

Table 3 Summary statistics for external social connections

Variable	Social connection linked			
	Yes		No	
	Median	Mean	Median	Mean
Success rate	1	59.64%	1	57.59%
Goal (\$)	5000	15,255.23	5000	23,414.45
Pledge (\$)	2690.07	11,814.85	2250	15,228.67
Progress (× 100%)	1.03	4.52	1.02	3.16
Number of backers	41	88	33	80

Table 4 Comparison of online followers and previous support for fundraiser

Variable	Campaign			
	Success		Failure	
	Median	Mean	Median	Mean
Avg. followers (external)	322	602	148	417
% of backed campaigns (internal)	0	57.79	0	43.06

Model 1: Fundraising status model (Logit), where F_i is a dummy variable representing the pledge status of project i , where 1 denotes successful funding—the capital raised has met the pledge goal—and 0 denotes a funding failure.

Model 2: Progress model, where F_i is the funding progress of project i , with 0 as the minimum.

Model 3: Number of fund backers model, where F_i denotes the number of fund backers in project i . The more fund backers there are, the greater is the attractiveness of the project.

Results and discussion

Statistical results

We identify external social connections using two indicators: (1) whether the crowd-funding project has a social link (1 = linked; 0 = else) and (2) the number of online followers. Table 3 shows that the external social connection linked groups perform better on funding success rate and funding progress than those without social connection links. Additionally, the social connection-linked group has more backers, implying the funding success of projects by drawing more fund backers. However, the group without social connection links is better than that on pledge goals and pledge amounts. The pledge goals of the social and non-social connection-linked groups were \$15,255.23 and \$23,414.45, respectively. Thus, fundraisers connected to their online social networks set lower pledge goals.

As shown in Table 4, the average number of followers for successfully funded and failed projects are 603 and 417, respectively. Hence, projects with successful funding have 44.36% more followers. Additionally, the fundraisers of successful campaigns have more external social connections and can obtain more monetary support from their followers, leading to a higher success rate.

As for the internal social connections, in Table 4, the “% of backed campaigns (internal)” refers to the proportion of fundraisers who have invested in other projects previously. Approximately 57.79% of the fundraisers of successfully funded projects had supported other projects earlier. Conversely, only 43.06% of the fundraisers of unsuccessful crowdfunding projects had done so. Therefore, fundraisers can build a wider range of social connections through more resource exchanges, contributing to successful fundraising in the future.

Table 5 presents the data statistics. The sample includes 108,463 projects, with a 59% project success ratio and 41% failed project financing. The higher project success rate collected in this corpus compared to those published by Kickstarter and others such as Mollick (2014) is because the dataset excludes the canceled, suspended, not available for public viewing, or hidden projects because of copyright reasons. With 18,130 excluded items, we collected a total of 126,593 raw corpora. The financing success rate is approximately 50%, similar to the results of most existing studies using this latter figure

Table 5 Descriptive statistics ($N=108,463$)

Category	Variable	Description	AVG	S.D	Median	Min	Max
Pledge result-related	<i>PledgeStatus</i> (1 = success)	Pledge status	0.59	0.49	1	0	1
	<i>NumBackers</i>	Backers count	85.30	136.67	38	0	999
	<i>PledgedRatio</i>	Pledged ratio	4.01	235.42	1.02	0	12.54
	<i>PledgedAmount</i>	Pledged amount in U.S. dollars	13,112.26	101,323	2541.1	0	1.03e + 07
Project-related	<i>NumUpdates</i>	Number of updates	7.66	10.94	4	0	301
	<i>NumComments</i>	Number of comments	62.95	1254.53	1	0	145,940
	<i>NumGoal</i>	Funding goal (\$)	18,356.11	383,830.7	5000	0.01	1.00e + 08
	<i>NumDurationDays</i>	Pledge duration days	34.70	13.62	30	1	91
	<i>NumPledgeLevels</i>	Number of pledge levels	9.57	5.84	8	0	227
	<i>Video</i> (1 = true, 0 = else)	Is an introduction video presented?	0.85	0.36	1	0	1
	<i>NumInvestmentHistory</i>	Number of times of investment	0.51	2.56	0	0	96
External social connection-related	<i>SocialConnected</i> (1 = true)	Is social network connected?	0.62	0.49	1	0	1
	<i>NumFollowers</i>	Number of followers	526.19	819.22	232	0	5981
Internal socialconnection-related	<i>NumPageRank</i>	PageRank of the nodes	0.0001	0.0086	0.0002	0	0.46
	<i>NumAuthority</i>	Authority of the nodes (in HITS)	0.0005	0.0013	0.0002	0	0.0343
	<i>NumHub</i>	Hub of the nodes (in HITS)	0.0001	0.0011	0	0	0.0459
	<i>NumDegree</i>	Degree of the nodes (in Centrality)	0.0001	0.0003	0.0001	0	0.0196
	<i>NumEigenvector</i>	Eigenvector of the nodes (in Centrality)	0.0017	0.0094	0.0001	0	0.2005

to obtain the financing success rate. However, as the internal and external social connections of these excluded items could not be observed and compared, we had to exclude the four project groups from our analysis, leaving us with 108,463 projects.

Results of external social connections

Table 6 shows the effect of external social connections on fundraising outcomes. The fundraising status model (logit) shows that external social connections improve the funding success rate ($\beta = 0.022^*$). Thus, if the fundraiser is connected to popular social media such as Facebook, it can significantly improve the funding success rate. As $\beta = 0.033^{***}$ for the number of online followers, fundraisers should provide their external social connections in their project profile and increase their online followers to promote the funding success rate.

The progress model (Model 2) suggests that providing external social connections does not alter funding progress ($\beta = -0.002$); the influence of online followers on funding progress does ($\beta = 0.004^{***}$). Thus, the more online followers, the better is the funding progress.

For the fund backers model (Model 3), the effect of external social connections on the number of fund backers is 2.318^{***} ; external social connections significantly increase the number of fund backers. Similarly, the number of online followers positively affects the number of fund backers ($\beta = 1.132^{***}$) but to a lesser extent due to the influence of providing external social links.

Results of internal social connections

For internal social connections, we compute the PageRank, HITS, and centrality for each node. Table 7 shows the effect of internal social connections on fundraising outcomes.

Table 6 Effect of external social connections on crowdfunding fundraising outcomes

Variable	Fundraising status (Logit)		Funding progress (Log)		Number of fund backers (Log)	
	Socially connected (1 = Yes)	Number of followers	Socially connected (1 = Yes)	Number of followers	Socially connected (1 = Yes)	Number of followers
<i>NumGoal</i>	-.574*** (.0054)	-.575*** (.0054)	-.130*** (9.7e-04)	-.130*** (9.7e-04)	14.85*** (.2356)	14.87*** (.2354)
<i>NumDurationDays</i>	-.448*** (.0169)	-.429*** (.0169)	-.074*** (.0035)	-.071*** (.0035)	-11.71*** (.8356)	-11.23*** (.8353)
<i>NumPledgeLevels</i>	1.336*** (.0146)	1.32*** (.0147)	.299*** (.0027)	.297*** (.0027)	56.07*** (.6575)	55.54*** (.6584)
<i>NumInvestmentHistory</i>	.154*** (.0163)	.145*** (.0163)	.113*** (.0032)	.112*** (.0032)	22.88*** (.7855)	22.69*** (.7852)
<i>NumFollowers</i>		.033*** (.0019)		.004*** (4.0e-04)		1.132*** (.0974)
<i>SocialConnected (1 = true)</i>	.022* (.0124)		-.002 (.0026)		2.318*** (.6309)	
Constant	3.596***	3.464***	1.22***	1.201***	-143.8***	-147.3***
Adjusted R ²	-	-	0.1802	0.1807	0.1213	0.1221
Observations	108,463	67,242	108,463	67,242	108,463	67,242

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, Standard errors in parentheses

Table 7 Internal social connections on crowdfunding fundraising outcomes

Variable	Fundraising status (Logit)			Funding progress			Number of fund backers		
	PageRank	HITS	Centrality	PageRank	HITS	Centrality	PageRank	HITS	Centrality
<i>NumGoal</i>	-.531*** (.0058)	-.5313*** (.0058)	-.5313*** (.0058)	-.1347*** (.0012)	-.1347*** (.0012)	-.1347*** (.0012)	19.42*** (.2984)	19.41*** (.2984)	19.41*** (.2984)
<i>NumDurationDays</i>	-.4131*** (.0187)	-.4131*** (.0187)	-.4131*** (.0187)	-.0706*** (.0042)	-.0705*** (.0042)	-.0705*** (.0042)	-12.25*** (1.069)	-12.25*** (1.069)	-12.25*** (1.069)
<i>NumPledgeLevels</i>	1.262*** (.0159)	1.262*** (.0159)	1.262*** (.0159)	.3172*** (.0033)	.3173*** (.0033)	.3173*** (.0033)	59.05*** (.8511)	59.07*** (.8512)	59.07*** (.8512)
<i>NumInvestmentHistory</i>	.0495*** (.0145)	.0493*** (.0145)	.0493*** (.0145)	.1011*** (.0032)	.1009*** (.0032)	.1009*** (.0032)	21.88*** (.8217)	21.84*** (.8217)	21.84*** (.8217)
<i>NumPageRank</i>	-8.7e-22 (4.6e-20)			-4.5e-23 (3.0e-23)			-4.6e-21 (7.7e-21)		
<i>NumAuthority</i>		1.2e-12 (5.8e-11)			3.1e-11** (1.2e-11)			8.4e-09*** (3.2e-09)	
<i>NumHub</i>		-3.2e-27 (1.7e-25)			-1.6e-28 (1.1e-28)			-1.7e-26 (2.8e-26)	
<i>NumDegree</i>			5.6e-29 (2.9e-27)			2.7e-29*** (9.8e-30)			6.7e-27*** (2.5e-27)
<i>NumEigenvector</i>			-2.0e-31 (1.1e-29)			-1.0e-32 (6.9e-33)			-1.0e-30 (1.8e-30)
Constant	3.543***	3.545***	3.545***	1.27***	1.27***	1.27***	-173.5***	-173.5***	-173.5***
Adjusted R ²	-	-	-	0.157	0.157	0.157	0.118	0.118	0.118
Observations	108,454	108,454	108,454	108,454	108,454	108,454	108,454	108,454	108,454

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, Standard errors in parentheses

Additionally, Table 7 shows that PageRank does not impact any of the models. However, the authority in HITS and degree of centrality positively influence funding progress and the number of fund backers. Authority is considered a node, with multiple nodes pointing to it. However, degree represents the sum of a node directly connected to other nodes (including out-degree and in-degree) (Chakrabarti et al. 1998). Therefore, fundraisers of crowdfunding projects should exert their influence and standing and improve their internal social connections through resource exchange. This finding concurs with that of Mollick (2014), who also noted the association of personal networks with crowdfunding success.

Predictive power of internal and external social connections

The interpretive and prediction models represent two analysis frames. The former analyzes and explains the factors that influence the occurrence of events post hoc. The latter is used to predict the trend or the result of events based on known factors (Sung et al. 1999). For example, although the impact of social connections on crowdfunding has been analyzed earlier, we did not test the predictive power of social connections. Nevertheless, when the interpretive and prediction model results are verified, we have sufficient grounds for reasonable implications for crowdfunding entrepreneurs.

As the fundraising outcome is binary in the *Nothing-or-All* funding model, a classification model is suitable (Wang et al. 2020a, b). We partitioned the dataset into a training set and test set with the same probability to ensure the smoothness of the test during cross-validation (CV). We used a tenfold CV; the data were randomly divided into ten parts—one was randomly selected as the test set, and the other nine data parts were

used for training. Subsequently, we used the algorithms to run ten experiments with different combinations and considered the mean outcome as the final prediction result, as shown in Table 8.

The value of the F1 score suggests that social connections (internal and external) promote the predictive power significantly, as shown using the KNN, decision tree, and MLP algorithms. However, AdaBoost, LR, Bayesian reference, and random forest exhibited limited improvement in the F1 score. This suggests that internal and external social connections cannot help improve the predictive power of all the algorithms. Overall, SVM provided the best performance across all four machine learning measures (F1, recall, precision, and accuracy).

The confusion matrix shows some differences in the accuracy of the SVM for positive (success) and negative cases (failure). The accuracy of the positive cases was higher than that of the negative cases (93.15% vs. 87.22%). Among the projects that failed in the prediction, SVM is more likely to predict failed campaigns as a success (12.78% vs. 6.85%)—the false positives are higher. To compare the difference between the predictive power of the internal and external social connections, SVM was further evaluated by the area under the curve (AUC), measuring the area under the receiver operating characteristic (ROC) curve from [0,0] to [1,1]. It provided an aggregated measure of performance across all possible classification thresholds. When the predictive model contains only control variables, AUC=0.89. After including the internal social connection-related variables, AUC=0.91. Likewise, when the predictive model included external social connection-related variables, AUC=0.95. Including the internal social connections only improves the predictive power of the model by 2.2%, whereas including the external social connections improves it by 6.7%. Fundraisers should build external social connections over their internal social connections. Including both external and internal social connection-related variables, AUC=0.97, a 9% increase in the model's predictive power.

Furthermore, when the difference in predictive power by project category was compared, as shown in Table 9, we obtained mixed results when including external and internal social connections. In general, social connections improve the accuracy of fundraising outcome predictions in art, design, and theater. Thus, in these categories, social

Table 8 Predictive power of internal and external social connections

Algorithm	Baseline (no social connections) model				Social connections (internal & external) model			
	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)
KNN	83.23	83.74	81.50	82.20	90.82	90.66	90.35	90.50
LR	79.31	78.72	79.31	78.91	79.33	78.75	79.35	78.94
Decision tree	82.53	86.10	84.18	80.25	82.12	86.77	83.81	84.78
Random forest	78.39	87.75	73.93	80.25	78.65	88.44	73.68	80.39
SVM	90.39	91.96	92.87	91.91	90.70	91.21	93.15	92.17
MLP	82.71	92.87	76.42	83.85	83.78	78.67	99.30	87.79
Bayesian	81.79	79.68	92.62	85.66	82.55	80.35	93.06	86.24
AdaBoost	81.61	81.09	89.58	85.12	81.67	81.04	89.80	85.19

Table 9 Comparison of predictive power by category (SVM)

Category	Baseline model				Social connections model			
	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)
Art	90.04	91.26	92.80	92.02	91.66	91.95	94.72	93.31
Comics	91.00	92.53	93.42	92.97	91.00	91.79	94.73	93.23
Crafts	89.28	91.89	89.47	90.67	88.78	89.22	89.22	89.22
Dance	91.99	94.05	96.73	95.37	89.20	90.44	97.01	93.61
Design	88.93	90.66	88.63	89.63	90.55	89.87	91.99	90.92
Fashion	90.18	92.17	86.18	89.08	89.92	91.86	85.87	88.76
Film & Video	91.20	92.04	92.53	92.29	91.44	92.13	92.69	92.41
Food	90.09	90.14	90.87	90.51	88.62	90.84	88.03	89.41
Games	91.53	92.07	92.50	92.29	90.96	92.60	92.85	91.71
Journalism	91.60	98.19	84.38	90.76	90.08	90.63	89.23	89.92
Music	92.11	93.84	95.22	94.53	92.61	94.05	95.80	94.92
Photography	90.88	90.74	91.02	90.88	88.10	88.83	89.58	89.20
Publishing	91.19	91.33	91.10	91.21	91.06	91.84	90.77	91.30
Technology	90.85	91.49	89.12	90.29	89.25	89.92	88.37	89.14
Theater	91.50	92.70	96.57	94.60	92.88	93.87	97.20	95.51

connections lead to successful funding predictions. However, in categories such as crafts and dance, including social connections contribute to lower accuracy. For instance, in crafts, the prediction accuracies for the baseline and social connection models are 89.28% and 88.78%, respectively. This suggests that the predictive power of social connections depends on the project category. Overall, SVM has good predictive power for dance, comics, art, music, and theater-related campaigns but poor predictive power for fashion-related campaigns.

We used the SVM method to compare the predictive power of the measures available on these projects to further analyze the univariate and break variables. Both univariate and the combination of different variables were detected. Table 10 shows the predictive power of these measures. Regarding the predictive power of the variables, *NumUpdates*, *NumComments*, *NumInvestmentHistory*, and *NumFollowers* have strong predictive power. The common trait of these variables is that they show entrepreneurs' social engagement. From the perspective of the prediction power of the break variables, the combination of project-related variables improves the prediction power the most. Nevertheless, the prediction power of the external and internal social connection-related variables is relatively weaker.

Contribution and implications

This study uses the representative online financing model—crowdfunding—to analyze the influence of external and internal social connections. This helps fundraisers exploit social connections, facilitating successful funding. When fund backers assess the value of a crowdfunding project, they often assess the quality of the project from multiple facets, notably project substance and the fundraiser profile (Wessel et al. 2016). Additionally, the project contents are typically specific, such as pledge goals, project category, pledge level, and funding duration (Wang et al. 2020). However,

Table 10 Predictive power of measures using SVM

Category	Variable	Univariate				Break variable			
		Accuracy (%)	Precision (%)	Recall (%)	F1 (%)	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)
Project-related	<i>NumUpdates</i>	75.60	78.30	80.87	79.57	81.04	83.06	85.08	84.06
	<i>NumComments</i>	58.74	58.74	100	74.01				
	<i>NumGoal</i>	62.45	62.35	91.05	74.02				
	<i>NumDurationDays</i>	59.59	60.23	91.88	72.76				
	<i>NumPledgeLevels</i>	59.67	59.81	95.55	73.57				
	<i>Video</i> (1 = true, 0 = else)	60.11	61.10	88.34	72.23				
	<i>NumInvestmentHistory</i>	58.74	58.74	100	74.01				
External social connection-related	<i>SocialConnected</i> (1 = true)	58.73	58.73	100	74.00	61.77	61.95	90.50	73.55
	<i>NumFollowers</i>	58.74	58.74	100	74.01				
Internal social connection-related	<i>NumPageRank</i>	49.03	25.99	28.67	27.24	58.74	58.74	100	74.01
	<i>NumAuthority</i>	50.69	48.26	90.26	64.27				
	<i>NumHub</i>	58.86	58.86	81.91	68.50				
	<i>NumDegree</i>	58.86	58.86	76.25	66.44				
	<i>NumEigenvector</i>	58.62	58.62	77.23	66.65				

research on the influence of fundraisers through social connections is scant, providing an opportunity for theoretical contributions and managerial implications.

Crowdfunding campaigns attract investor attention in one of two ways: (1) advertising the creativity behind the project—the novelty of the idea; (2) highlighting the fundraiser’s qualifications—the entrepreneur’s profiles, such as educational background, skills, awards, credit, and reputation (Wang et al. 2020). However, previous studies have not focused on social connections. Our study expands the extant research on the impact of fundraisers’ profiles and improves investors’ quality evaluation model.

The discussion on crowdfunding is from a project quality perspective. For example, better linguistic features enhance project quality (Parhankangas and Renko 2017). Likewise, a large-scale exposure and resource exchange may enhance potential investors’ subjective project quality assessment (Kromidha and Robson 2016). This study enriches signal quality display by bridging internal and external social connections to sharpen the project quality model. Additionally, this study analyzed the effect of social connections by project category. As the project quality evaluation criteria depend on the category and hence on the impact of social connections, it is appropriate to measure crowdfunding projects using differentiated standards. Therefore, fundraisers should selectively leverage their social connections to target specific project categories.

Given the limited research on the impact of the entrepreneur's social connections, studies have shown that several social relationships can help budding entrepreneurs achieve success. The popular press attributes this resource to the presence of social capital. Social capital developed within an online platform can render the serial crowdfunded campaigns more successful than those launched by novice crowd funders, mainly when the fundraiser is a KOL. However, this form of social capital is only a weak and temporary substitute for internal social capital built by backing other campaigns (Buttice et al. 2017). As for external social capital, the number of followers found on the external social network can significantly increase the possibility of successful funding, concurring with Zheng et al. (2014). Nevertheless, this conclusion needs to be guarded as we draw an equivalence between social capital and social connections, not necessarily true and requires further validation.

Online product-quality signals are reflected in many aspects, and the word-of-mouth effect formed by online reviews and cyber connections is the most widely discussed signal quality (Nam et al. 2010). These studies on signal quality focus on the signal content but not on signal transmission. Effectively transmitting the signal and getting the user to receive and understand the signal accurately have become prerequisites for the signal to exact a fair role (Freedman and Jin 2014; Vismara 2016). Social connections have signaling quality; stronger and more verifiable network centralities are associated with a higher likelihood of a project being funded and a lower defaulting risk (Lin et al. 2009, 2013). Further, the micro-level social network structure and network connections expand the users' observation channels for effective signals (Abrahamson and Rosenkopf 1997). Thus, our study validates the positive effect of social connections on signal quality and concurs with Mollick (2014) and others.

Based on resource exchange, we divided social connections into external and internal social connections. Prior studies indicate that social connections promote successful funding by arguing that social connections lift project visibility and thus attract more fund backers. However, these studies neglect fundraisers' engagement with social media. Some fundraisers, believing in dialogic transmission systems, provide social connections, while others deliberately hide their online connections because of privacy concerns. Furthermore, lurking is a common phenomenon in external social connections (Chaboud 2019). Therefore, the value of external social connections (e.g., online followers) should be discounted. While internal social connections based on resource exchange are more reliable, few studies have focused on the relative effects and differences. Moreover, the number of online followers can vary, leading to differences in the fundraisers' online influence. This study suggests that entrepreneurs provide social connections and gather more online followers, as Clauss et al. (2020) suggested. Network centrality and the fundraisers' authority promote user participation. This study also highlights the role of reciprocity in crowdfunding through internal social connections.

Most extant studies focus on external social connections while ignoring the internal social connections formed by resource exchange. Entrepreneurs could establish connections with other users by sharing a common investment interest, notably in similar project categories from the internal social connection perspective. However, this relationship may be fragile. From the weights of the nodes, we find that only the authority of HITS and the degree of centrality positively impact funding performance. Moreover,

nearly every crowdfunding project is given the same treatment online by crowdfunding platforms, although differences exist in the evaluation criteria between project categories. For example, fund backers often pay more attention to fundraisers' profiles for art-related crowdfunding projects. From this perspective, the choice of an online outreach vehicle should reflect the nature of the project category. Our study endeavored to use actual data.

Practically, for Kickstarter, the revenue stream for a reward-based crowdfunding platform is derived from the fees collected on successfully funded projects. Therefore, attracting more fund backers improves the profitability potential of the platform (Gallo 2021). Crowdfunding platforms working on this approach should thus encourage fundraisers to proactively grow their online presence and stretch their sphere of influence.

Additionally, this study shows that the network centrality measures of the internal network positively affect the funding progress model and fund backers models, offering a refreshing perspective for improving financing performance. Given the value of internal social connections and centrality measures, it is reasonable to suggest that crowdfunding entrepreneurs enhance their social network centrality. In social networks, centrality refers to the degree of a person's centrality in a social network. A numerical value often denotes the degree for the ease of representation. Transposing to the crowdfunding platform, the fundraiser can establish internal social connections and occupy a central position by applying the following methods. First, the fundraiser can increase the frequency of investments and create connections through resource exchange. Frequent resource exchange with numerous users helps improve the centrality of a node (Hoffman et al. 1990). Second, the fundraiser can strive to become a recognized expert in a specific field. Experts represent more influential nodes by exuding more authority and are more likely to become the center of the network (Klein et al. 2004). Third, the fundraiser can focus on the role of an opinion leader. Opinion leaders influence the opinions of others. In addition to the internal connections formed through resource exchange, opinion leaders also occupy the centrality of the network (Li and Du 2011). Therefore, the formation of the entrepreneur's leadership plays a role in improving the fundraising outcomes of crowdfunding projects.

Conclusion

By comparing the effects of external with internal social connections on fundraising outcomes and predictive power, this study has unraveled some findings using data from Kickstarter. Both internal and external social connections positively affect fundraising results, but their relative effects differ. The predictive power of external social connections exceeds that of internal social connections. Therefore, entrepreneurs should prioritize external social connections and stay at the center of the network. The internal social connections formed by resource exchange are fragile, whereas the external links in online followers are stronger. This theoretically answers the weight between the internal and external social connections and explains the signaling of online projects.

The results validate the value of social connections for successful fundraising. Fundraisers need to actively feed information through their social connections and increase their online influence to attract more fund backers and increase the funding success rate of their crowdfunding projects, especially when the project category

appeals to social connections. Further, online entrepreneurs should maintain external social connections effectively through Facebook or LinkedIn and expand their online followers based on Twitter.

While the mutually exclusive characterization of social connections are used, there is still considerable scope for future research. First, this study assumes that the overall quality of the projects is stable or that crowdfunding projects launched with different social connection attributes are similar. This assumption may not be valid. Project quality may be subject to social connections. Although we have used extensive data (108,463 campaigns) and adopted many control variables, these measures can only address the quality concern in a limited way and are restricted to the Kickstarter platform. Project quality is a broad topic and cannot be fully represented by control variables or platform agnostics. Second, we divide social connections into mutually exclusive and identically independent internal and external social connections and use a directed graph model to build the network structure. Additionally, there are other network construction methods, such as undirected graphs—another future research direction. Third, this study uses the connection data from social platforms regarding external social connections, such as Facebook and Twitter, as proxies. However, owing to the lack of deeper data granularity, we could not analyze the differences between the generational, geographic, and cultural settings of the communities. These settings may skew funding outcomes. This is another direction for future research. Finally, the lurking intention is an important issue in the online community. The external social connections used in this study are likely to exhibit lurking behavior, highlighting another potential research avenue.

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Authors' contributions

This work was conducted in collaboration with all authors. Conceptualization: Lihuan Guo; literature review: Wei Wang; methodology and data analysis: Yenchun Jim Wu, Lihuan Guo; Original draft writing: Mark Goh, Lihuan Guo; Review and editing: Yenchun Jim Wu, Lihuan Guo; Project administration and funding acquisition: Wei Wang, Yenchun Jim Wu. All authors read and approved the final manuscript.

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Availability of data and materials

Source of data sets are available from the authors on reasonable request.

Declarations

Competing interests

The authors declare that they have no competing interests.

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