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Providing a dynamic investment model for financing knowledge-based companies with a data mining approach

Vahid Godarzi[a], Mohammad Mashhadizadeh[b,*], Sayyed Mohammad Reza Davoodi[a]

[a]*Department of Management, Dehagan Branch, Islamic Azad University, Dehagan, Iran*

[b]*Department of Management, Mobarakeh Branch, Islamic Azad University, Mobarakeh, Iran*

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Abstract

The development of computer technologies and automated learning techniques can make decision-making easier and more efficient. In the field of machine learning, where computers always make decisions or propose suggestions for proper decision-making, there exist many decision-making techniques such as decision trees, neural networks, etc. Flexibility and comprehensibility are one of the advantages of the decision tree model. The decision tree can provide the possible options, goals, financial profit, and information needed for an investment for the managers better than any other tool. The decision tree is one of the most applicable data mining algorithms. On the other hand, crowdfunding in knowledge-based companies is a new financial phenomenon in online financing of innovative projects and knowledge-based businesses that reduces financing costs and problems in addition to changing the nature of the investment. There are four types of crowdfunding in knowledge-based companies namely donation-based, equity-based, lending-based, and reward-based. Reward-based crowdfunding can be considered the most publicly familiar crowdfunding model, where backers will actively participate in the product development process along with investment. Low-cost crowdfunding websites act in the projects as an online mediatory between the initiators and the sponsors. Therefore, the factors affecting the success of crowdfunding were evaluated in this research regarding the initiators' performance and the sponsors' feedback, and the significant attributes were presented in the form of a decision tree structure using the data mining technique. The results reveal that the best performance of initiators is related to the field of direct investment attraction with 92% accuracy of the decision tree with the most important attributes of "number of updates during the investment period" and "number of dynamic technical and tactical analyses".

Keywords: Initiators and sponsors, Crowdfunding, Data analysis, Knowledge-based Companies, Decision tree
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1 Introduction

One of the interesting classification methods is to build a decision tree including a series of decision nodes connected by branches. The decision tree starts at the base with a single node and extends to the many leaf nodes. Starting from the root node, which is conventionally placed at the top of the decision tree diagram, the properties are tested in the decision nodes and each output leads to an observation. Then, each branch is connected to another decision

*Corresponding author
Email addresses: vahidgodarzi2011@gmail.com (Vahid Godarzi), moh.msh49@gmail.com (Mohammad Mashhadizadeh), smrdavoodi@alumni.ut.ac.ir (Sayyed Mohammad Reza Davoodi)

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node or a terminating leaf node. In recent years, crowdfunding has emerged as a new financial mechanism without the need for complex and difficult traditional investment methods such as bank loans. In this emerging phenomenon, entrepreneurs and initiators present their creative, new, and innovative ideas and plans in the form of a project through crowdfunding platforms to a large number of potential sponsors to implement the projects through investment and crowdfunding.

The concept of crowdfunding derives from a wider phenomenon called crowdsourcing, which is defined as "using the crowd to get ideas, feedback, and suggestions for the development of the organization's activities" [9, 34]. Crowdfunding is defined as a public appeal in exchange for rewards or shares to support initiatives with specific goals, typically via the internet [7, 8, 22]. Crowdfunding continues to grow globally with the evolution of web technology; there are more than 450 crowdfunding frameworks in the world [12].

The total amount of crowdfunding capital is expected to have raised around $34.4 billion in 2015, up from $16.2 billion in 2014. Reward-based crowdfunding is the largest online crowdfunding framework and grows faster than the other crowdfunding types in knowledge-based companies.

Reward-based crowdfunding can be considered the most publicly familiar crowdfunding model, where backers will actively participate in the product development process along with investment [26]. Further, it is financing that provides non-monetary rewards to sponsors [2, 9, 28]. Kickstarter is the most popular rewards-based funding website in the United States, with more than 35 million sponsors in 20 countries around the world, and it has performed 118,362 new projects with $2.8 billion in the capital. However, such projects' success rate is less than 50%. For instance, the success rate of Kickstarter in 2016 is 35%, which has decreased by 8% compared to 2014.

The recognition of factors affecting the success of the crowdfunding campaigns to a better understanding of the dynamics of investment as well as to improve their success in knowledge-based companies. To obtain the determining factors in the success of crowdfunding, first, its goals are stated and then, the dimensions of success are defined and examined.

In knowledge-based companies, the initiators' goal is to attract a large number of potential sponsors in the relevant field and finance them. The sponsors' goals of funding the initiators' projects are divided into two categories of financial and non-financial incentives. Sponsors with non-financial incentives include the minimal group of them who support the initiators' campaign regardless of their profit and level of defined rewards. They support the initiators' campaign with a participative motive. Most of these sponsors are the initiators' families and friends who act as angel investors and play a significant role in the success of the crowdfunding project in the early stages. Sponsors with financial incentives include the maximum group of supporters who look for financial and capital interests in their investments. Regarding the innovative products and services defined in the form of bonus tiers, this group of sponsors acts as customers who pre-purchase a new product or service.

Therefore, the goals of initiators' and sponsors' roles are defined based on the factors affecting crowdfunding. For initiators, the success of crowdfunding (before project crowdfunding) depends on the attraction of financial support from potential sponsors in knowledge-based companies. On the other hand, from the sponsors' viewpoint, the success of crowdfunding (after the crowdfunding of the project) is related to the timely and proper delivery of selected rewards.

No considerable research has been done on crowdfunding success factors before crowdfunding (from the initiators' viewpoint) and after crowdfunding (from the sponsors' viewpoint) for knowledge-based companies.

The successful initiators' campaign pages during the campaign period for knowledge-based companies are examined in this research and important and outstanding attributes are extracted in terms of their performance. Then, in the case of the sponsors' feedback, the influence of social innovative networks (Facebook and YouTube) on potential supporters during the campaign period. For this purpose, the Gross Rating Point (GRP) criterion was used for the first time.

2 Review of research literature

The Internet and cyberspace communications have revolutionized various aspects of our lives. Online platforms, such as social networks, which are generally known as a factor in the transformation of the flow of information and cultural content, have also revolutionized the field of innovation and creative industry [33]. A new type of non-bank lending has been developed by the emergence of the internet that uses the community to provide the required credit, and this is not limited to specific geographic and economic boundaries by the use of the internet. Crowdfunding can be considered sharing classified advertisements on the internet, with the difference that, in crowdfunding platforms, entrepreneurs can provide needed financial resources in addition to advertising their business model. According to

"Wong and Wong", this movement has only affected a small part of the financial provision policies, mostly at the micro level. But it can be predicted that this procedure can considerably affect the current approach in the future. Undoubtedly, the mentioned movement could succeed in many other fields by reducing the levels of intermediaries in the funding process, in addition to the mentioned cases related to financial technology. Among these cases, we can refer to the active presentation in the secondary markets of trading securities, shares, and bonds; like what the "Second Market" company does in America.

Financial data analysis is one of the other areas developing through financial technology. "Markit" company in England is considered one of the successful companies in this field. Providing an independent database, processing loan transactions, creating technology platforms, and managing them based on the customers' needs are other advantages of using financial technology, and the information extracted from these services and products can be used by banks, investment funds, insurance companies, asset management companies, central banks, regulatory bodies, and accounting companies.

The manner of using financial technology in banking businesses is one of the issues attracting the attention of information security companies in the field of online banking. Indeed, these companies aim to provide financial and payment services for their depositors. It is worth mentioning that online banks in America have been developed by non-banking financial institutions such as brokerage and insurance companies. In general, four main factors are effective in developing various successful financial technology businesses. The first factor is providing better access. Most of these businesses offer smartphone-based platforms that pave the way for micro-investing at any time and place. Moreover, they reduce barriers such as the minimum required investment, to provide the possibility of entering the investment world for new customers who have not yet entered this market. The second factor is the use of mass data in financial technology. For instance, Invoice England, as an active company in the field of financial technology, presented an online business platform in 2011 through which small- and medium-sized businesses can discount their unpaid invoices to provide their working capital. At the present, invoices worth about 10 million euros are exchanged every month in the mentioned company. Further, this company provides loans worth 50 billion euros for small- and medium-sized businesses, developed by the British government.

Crowdfunding frameworks integrate three entities, i.e., initiators (founders), sponsors (investors), and crowdfunding platforms that act as an intermediary between initiators and sponsors. Further, crowdfunding platforms are categorized into four categories in terms of process complexity and risk diversity, including donation-based financing, reward-based financing, loan-based financing, and share-based financing [2, 9, 17, 28, 30, 31]. Figure 1 represents the financing frameworks and components along with the criteria for measuring sponsors' feedback in social networks.

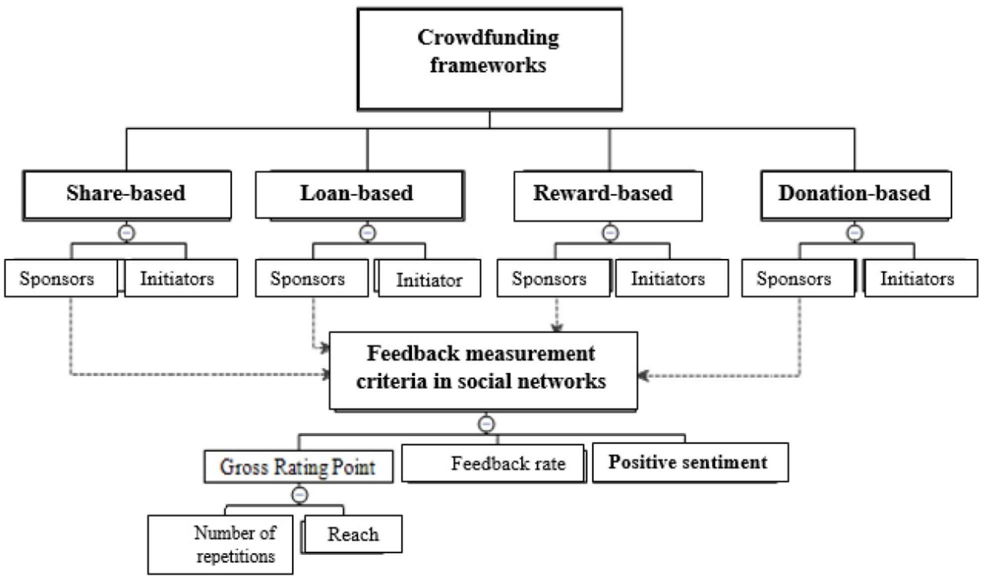

Figure 1: Literature review of financing frameworks and criteria for measuring sponsors' feedback

2.1 Financing frameworks

2.1.1 Donation-based financing

Role of initiators

Donation-based crowdfunding cannot be considered a common way to finance startups with financial incentives. Therefore, entrepreneurs should use other crowdfunding methods to finance their projects [9]. Usually, donation-based financing in the form of grants can be applied in the early stages of the campaign [32].

Role of sponsors

Supporters of donation-based crowdfunding projects aim to develop intangible products and social welfare without profitability incentives [9]. In donation-based financing, supporters' activities are accomplished without investment incentives and without the desire to receive rewards, taking into account the factors of empathy and solidarity. In this financing, both complexity and risk processes are declined, and sponsors are considered donors [16].

2.1.2 Reward-based financing

Role of initiators

Analyzing and examining successful Kickstarter projects from 2009 to 2022, researchers found that successful projects provide more reward rows and the initiators' social information plays an important role in the project's success [25]. Investigating the number of fake likes on Facebook through the campaign in the Kickstarter platform reveals that the number of fake likes has a short-term positive effect on the number of sponsors, and then their number considerably decreases so that its number becomes less than the time when unreal social information is uploaded. Therefore, it would negatively affect the number of campaign sponsors [39]. Social networking websites of Twitter and Facebook are considered two important platforms for initiators to connect with fans and friends who want to cooperate in financial and informational support. Furthermore, the results showed that private networks and the quality of initiators' basic projects have a relationship with the success of crowdfunding [28]. A comparative study of objective data collected from the Chinese crowdfunding website of Demohour and the Kickstarter American crowdfunding website reveals that the entrepreneur's social network relationships, commitments to other entrepreneurs, and sharing the financing projects among the entrepreneurs and sponsors have a significant effect on the financing performance in these two countries. They also showed that the predictive power of social capital in all communicational, structural, and cognitive dimensions is stronger in China compared to the United States [41].

Role of sponsors

In reward-based financing, investors and sponsors behave like customers since the main business model in this platform is in the pre-purchase form [11, 28]. Also, when the investor checks whether to finance pre-purchase projects, they behave like customers in online purchases [28]. Pre-purchase crowdfunding is the most common type of crowdfunding. In this model, customer payments are done in a pre-purchase form in such a way that if the startup produces a product, the customer buys that product at a price lower than the market price [9].

The geographical distance between an initiator and potential sponsors plays an important role in crowdfunding. Local sponsors finance more likely in the early stages and pay less attention to others' decisions [25].

The researchers showed that sponsors are motivated to collect rewards, help others, and support agents. Therefore, financial or product advantages make many sponsors participate in the projects because they compare the value of the rewards with their financing. Moreover, they are inclined to receive the new product or service before its public production [16]. Studies reveal that sponsors expect valuable project information to be constantly shared with them in exchange for their financing [15, 16, 24]. According to the data collected from the Sellaband platform (in the field of financing music and music albums), the success of the project in crowdfunding depends on the sponsors' financial participation. Therefore, it is of special importance to study the perception of their behaviors and incentives [2]. Regarding the data collected from Demohour crowdfunding website in China, sponsors' satisfaction is one of the important criteria affecting the success of crowdfunding projects, which positively affects the refinancing of the projects by sponsors and makes them trust in the crowdfunding framework [40]. Researches show that the sponsors' support and social participation in setting up their friends and family's projects are due to basic reasons and a shared sense of value. Therefore, sponsors do financing concerning ideology-based common affairs [16, 25].

2.1.3 Loan-based financing

Role of initiators

Loan-based crowdfunding is the technical and financial leverage to communicate with lenders (sponsors) and borrowers (initiators), which is called peer-to-peer lending [38]. According to these systems, the borrower's (initiator) social relations have a positive relationship with the probability of success and interest rate [14].

Role of sponsors (investors)

In loan-based crowdfunding frameworks, most investors need the project builders' roadmap [3, 11]. In loan-based platforms, investors are usually more inclined to stories that represent investment as an opportunity to help people than stories that represent investment as a business opportunity and show less interest in the later ones [4].

2.1.4 Share-based financing

Role of initiators

Investigating the Investor share-based crowdfunding website in Finland reveals that the campaign success depends on the attributes of the financed campaigns and the use of social and private networks by the initiators [27].

Role of sponsors

In share-based crowdfunding frameworks, like loan-based crowdfunding systems, most sponsors need the project builders' roadmap [3, 11].

2.2 Measurement criterion of the effects of virtual space in the crowdfunding campaign

Gross Rating Point (GRP) is a criterion for measuring the chance of a campaign's impact. GRP is the criterion for measuring the advertising audiences and is equal to a percentage of a target demographic that is reached by an ad (known as reach), multiplied by the number of times they've seen the ad in a given campaign (known as frequency) [21, 23]. GRP is a general measure of the volume of a campaign's advertising that is exposed to the audiences through a specific media during a specific period, or it is a cumulative measure of people's ratings that is used to measure a specific marketing campaign or program [13].

2.2.1 Reach

In social media, reach refers to the potential audiences of a message or the number of people who can be exposed to the message. The quantitative size of the target audience is required to be specified for successful campaigning. Reach is essential for the campaigns since it helps to determine the potential impact of the social page.

Reach is divided into two types: numerical reach and percentage reach. Numerical reach is equal to the number of target audiences related to your advertising, and percentage reach refers to the frequency of people who have access to your campaign [21]. Reach is the percentage of the population covered by an advertising program [10].

Reach refers to the percentage of the target audience that will likely be exposed to an advertisement in a certain period or the number of people covered by a campaign [23]. Reach is the number of people (target audience) exposed, at least once, to a media message (advertisement) during a certain period [6, 20, 36].

2.2.2 Frequency

Frequency is the average number of times your ad is displayed in the media. Frequencies are often defined as weekly, yearly, or the duration of a campaign. The frequencies usually are considered a period of four weeks or 28 days [21]. It is the number of times that unique people (target group) are exposed to a specific advertisement during a certain period [6, 10, 20, 23].

2.2.3 Engagement rate

The engagement rate is obtained by dividing PTAT (the number of people who like, share, and comment on posts) by the total number of likes [1, 19, 29, 35].

$$\text{Engagement Rate} = \frac{PTAT(\text{Likes} + \text{Shares} + \text{Comments})}{\text{Total Likes}} \tag{2.1}$$

The engagement rate represents an overall view of each fan's engagement rate. The high value of this number indicates the high quality of the pages from the fans' perspective [29]. Measuring customer engagement in online social networks is of special importance in better understanding, effectiveness, and profitability [37].

2.2.4 Positive Sentiment

Positive sentiment is calculated by dividing the sum of likes, shares, and positive comments by the sum of all posts and comments [5, 37].

$$\text{Positive Sentiment} = \frac{\text{Likes} + \text{Shares} + \text{Positive Comments}}{\text{Total Posts} + \text{Total Comments}} \tag{2.2}$$

3 Methodology

The successful and unsuccessful campaigns of the Kickstarter crowdfunding website are examined in this research to extract the factors affecting the success of crowdfunding in knowledge-based companies. Then, the social networks related to the initiator campaign are analyzed during the campaign period. After examining the main attributes obtained by the expert, the CRISP data mining steps are applied to design an appropriate model.

3.1 Population and sample

In total, 250 data sets were collected from January 2019 to January 2022 in the three areas of accelerators in knowledge-based companies, direct investment, and growth centers of successful and unsuccessful campaigns in Iran.

3.2 Research tools

Data mining is an interdisciplinary field in which various fields such as databases, statistics, machine learning, and other related fields were integrated to extract valuable information and knowledge latent in a large amount of data. Also, data mining is considered the analysis of a large amount of data to discover meaningful patterns and rules. The process of data mining is also called knowledge discovery in data [18].

The main data mining methods are categorized into descriptive and predictive ones. Descriptive functions specify the general characteristics of data. The purpose of the description is to find patterns in the data interpretable by humans. Predictive functions are used to predict their future behavior. Prediction means using several variables or fields in the database to predict the future or undetermined values of other variables of interest. Clustering and classification are the most common descriptive and predictive methods, respectively.

In classification methods, some observations are already labeled as a category. These labeled data are divided into two categories of training and testing data. Applying data mining methods, a model is developed on the training data. Further, for evaluation, the test data label is predicted using this model and is compared with the real values to determine the model's accuracy. Common methods of decision tree classification include Bayesian classification, backpropagation neural networks, and support vector machines.

Decision tree learning is one of the most common machine learning techniques widely used in machine learning problems due to its simplicity and efficiency. A decision tree shows a structure where the leaf nodes represent the categories and the branches represent the seasonal structures of attributes resulting in these categories. Decision trees can generate human-understandable descriptions of the relationships existing in a dataset and are used in classification and prediction tasks.

3.3 Procedure

CRISP data mining methodology is the most popular method used to conduct data science projects. In this research, data mining was done by applying this method. CRISP data mining methodology includes six steps Business understanding, data understanding, data preparation, modeling, evaluation, and deployment.

3.4 Business understanding

The business goal, business conditions objectives, and data mining purpose represent the purposes of the project in technical terms.

Business Success Criteria: Defined project output describes business success objectives.

Data mining success criteria: it expresses the criteria for the successful output of the project in technical terms. It is necessary to describe the objective condition based on individuals' subjective judgments.

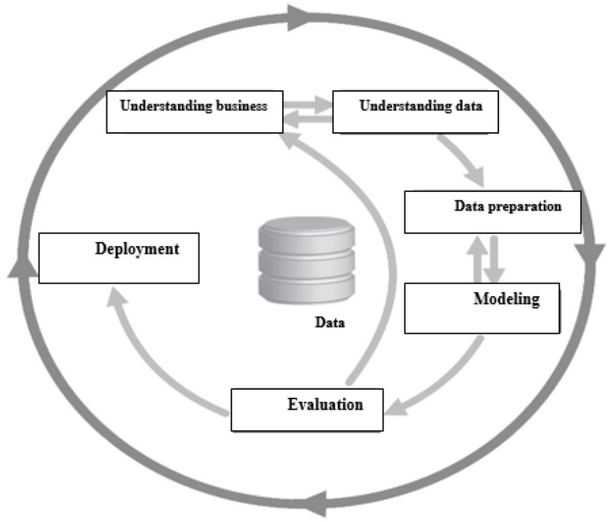

Figure 2: CRISP data mining methodology

3.5 Data understanding

The needed data sources along with the required methods and data background are used to study the intended issue regarding the spatial and temporal condition. The description of the obtained data includes the data type and format, the amount of data (including the number of records and attributes of each table), and identifying the characteristics and other extracted attributes. Therefore, at this stage, the obtained data are examined to achieve the research goals. The distribution of key attributes such as data mining predictive goals, relations between variables, significant relationships between subsets, and simple statistical analysis is done in this step. These analyzes can directly meet the data mining goals. It describes the results of data exploration including the primary findings and hypotheses and their impact on the rest of the project. If the data is appropriate, graphs and charts would be used to show the data characteristics. Orange software and Python programming language are used to do data analysis in different areas.

Data quality assessment: In this stage, the numerical data value, missing data, and whether the data sufficiently cover the project requirements are assessed. Then the results of data quality verification are reported and possible solutions are provided if needed. The data quality solutions depend on data and business knowledge.

3.6 Data preparation

Data selection: In this stage of the project, we decide on the data to be analyzed. The decision-making criteria related to data mining objectives include data quality and technical restrictions (limitations in the amount and type of data). Therefore, data selection involves selecting the attributes (columns) and records or characteristics (rows).

Data cleaning: Increasing the quality of data to the intended level is done by applying selective analysis techniques, which include the selection of data-cleaning subsets, replacing appropriate defaults, and, more importantly, estimating missing data through modeling.

Data transformation: This stage involves operations required for useful data preparation such as creating derived attributes, inserting new (attribute) records, and transforming values for existing attributes.

Data reduction: Methods that integrate the information extracted from multiple databases and tables to create new records or attributes.

3.7 Modeling

In the first step, the required real modeling method is selected. Before making the final model, the mechanism and method of quality assessment, and model validation should be developed. The developed plan is used for training, testing, and evaluating the model and its main component is to determine how to divide the existing data set into training, testing, and validating data. In this stage, the modeling tools are implemented on the available data to produce one or more models. In the evaluation stage of modeling, the constructed model is rated and assessed according to the evaluation criteria. Business objectives and business success criteria are taken into consideration as much as possible.

3.8 Evaluation

In this stage, the model is evaluated based on the business objectives. The evaluation process involves the evaluation of other generated data mining results, too. The data mining results include models that are necessarily related to the main objectives of the business as well as other models not necessarily related to these objectives but reveal potential challenges, information, and future decisions. Therefore, the results of the evaluation related to the business success criteria and the compliance of the present project with the primary objectives of the business are expressed in this stage. The process and lost effective measures that should be repeated are reviewed in this stage.

4 Findings

The data analysis is done in two classifications of initiators' performance and potential sponsors' feedback. In the case of initiators' performance, the attributes related to the initiator's activities on the internal campaign page, Instagram, and YouTube social networks during the campaigning period are evaluated, and the most important effective factors are recognized. In the next step, determining the factors affecting the success of internal campaigns crowdfunding regarding the initiators' performance to achieve the maximum financing amount is one of the objectives of the success of initiators' performance. In data mining success criteria, better understanding and recognition of the structure of financed (funded) campaigns and determining the important campaign financing attributes (being funded) to attract more sponsors in the initiators' campaign are the objectives of data mining success.

4.1 Data understanding

The dataset extracted from the domestic websites in the case of initiators' performance included 130 accelerator campaigns, 60 internal and direct investment campaigns, and 60 growth center campaigns.

4.2 Data description

Of a total of 46 attributes extracted, 26 items are related to the initiators' performance in the fields of the gold market, stock exchange, and investment. Further, the variable of attributes is fixed and stable for all present classifications.

4.3 Data discovery

In this stage, the target attributes of the data mining project are distributed and the sample is statistically analyzed. The target variable (entitled class) is defined with two values of zero and one to evaluate the project financing on the internal website. If the sponsors' funding value is greater than or equal to the campaign's target value, the project is considered funded (It has successfully funded the project) and is classified in class one. Otherwise, the project is unfunded (it has failed to fund the project) and is categorized in class zero. Table 1 represents the descriptive statistics of the attributes extracted based on the minimum, maximum, mean, and standard deviation in the categories of accelerators, direct investment, and growth centers for statistical data analysis.

4.4 Data quality assessment

The quality of data and their informational value are of special importance in providing desirable results through different methods. Table 2 represents the attribute importance criteria including information-based criteria (Gini Index, Gain Ratio, and Information Gain) and statistical criteria (ANOVA, Chi-Square) related to the initiators' performance in the case of accelerators. The data analysis reveals that all the attributes are valid and there are no attributes without numbers.

As is observed in Table 2, the number of updates, the number of photos in the updates, the number of responses, and the number of photos on the campaign page have the highest values of the attribute selection criteria and are located in the nodes of the decision tree of data mining in the case of accelerators.

Table 1: Descriptive statistics of accelerator campaigns, direct investment, and growth centers

Category	**Accelerators**				**Direct investment**				**Business incubator**			
Feature	Min	Max	Mean	std.dev	Min	Max	Mean	std.dev	Min	Max	Mean	std.dev
Goal	17500	5500000	190651.5	509915.7	3600	5000000	130871.7	644234.1	1050	150000	18724.85	16.95
Funded	77	6225354	497688.5	926273.3	11	1924018	87565.27	289600.4	1542	665725	45029.03	96014.72
Rate of Funding	0	105.634	6.831	14.062	0	38.48	2.717	6.459	0.106	22.343	2.759	3.87
Backers	5	105857	3010.69	9883.146	–	–	–	–	–	–	–	–
Duration (day)	29	60	37.75	8.846	23	60	33.983	8.831	25	60	32.867	6.756
Updates	0	28	7.852	5.262	0	37	6.483	6.066	0	51	10.9	8.966
The First Update After Launch (day)	0	60	5.477	11.045	0	60	10.1	15.988	0	60	3.917	8.662
The Number of Answers	0	75	7.352	14.535	0	78	8.133	16.425	0	215	15.617	32.148
The Number of Photos on Updated	0	100	9.914	13.744	0	70	8.883	13.17	0	105	20.067	25.41
The Number of Video on Updated	0	12	1.18	1.867	0	16	1.167	2.823	0	4	0.533	0.892
The Number of Rewards Row	0	64	12.219	7.978	1	45	16.233	8.282	7	35	17.167	6.916
Lowest Price of Founder's Product	9	2999	299.57	469.439	1	645	41.1	82.328	5	50	19.9	8.756
Rewards of Founder's Product	1	60	10.031	7.707	1	44	14.317	7.604	5	33	15.083	6.808
Rewards of Others Product	0	17	2.203	1.888	0	9	1.917	1.69	0	4	1.917	1.124
Limited Rewards of Founder's Product	0	54	7.008	7.741	0	28	7.983	6.675	0	27	7.817	6.614
Estimated Delivery (day)	0	1440	147.813	143.826	28	780	108.767	123.41	28	330	128.467	70.802
The Number of Campaign's Video	0	11	2.844	2.079	0	7	1.533	1.334	1	4	1.333	0.752
The Number of Campaign's Picture	1	67	22.234	11.196	0	58	19.717	13.515	2	62	28.067	15.372
The Number of FAQ	0	49	11	10.461	0	16	1.333	2.814	0	8	1.2	1.955
The Number of Funded Campaigns	0	45	3.398	6.213	0	43	3.661	6.624	0	38	9.367	9.384
The Number of Posts Facebook	1	187	28.055	27.113	0	146	33.233	31.422	0	108	32.9	23.652
The Number of Previous Posts Facebook	0	300	56.93	88.703	0	300	197.85	133.415	0	300	159.367	132.661
The Average of Facebook's Fans	0.241	2979	99.844	321.102	0	4850	593.11	1036.933	3.067	738.048	114.776	163.982
The Number of Youtube's Video	0	19	2.398	2.557	0	35	1.967	5.327	0	16	1.283	2.233
The Number of Previous Youtube's Video	0	25	2.165	3.864	0	300	14.017	54.078	0	300	14.267	45.281
Youtube's Subscribe	0	93732	3523.77	12467.69	0	622559	11541.77	80515.11	0	1000000	17627.7	129044.8

4.4.1 Data preparation

Data selection: The rows of the data table represent the records or titles of successful and unsuccessful campaigns in the three areas of accelerators, direct investment, and growth centers. The columns of the data table related to the extracted attributes were defined according to the initiators' performance goals. The first column in Table 1 indicates the extracted attributes based on the initiators' performance and the potential supporters' feedback.

Data cleaning: in this stage, the attributes of "funding rate" and "collected amount" are removed along with the attribute of "number of sponsors" due to their predictability since they represent the success of project funding.

4.4.2 Modeling

Modeling technique selection: The decision tree data mining technique is the main method applied in formulating the model of this research.

Test design: In classification algorithms, the primary dataset is divided into two categories of training datasets (70% of the initial data) and the testing dataset (30% of the initial data).

Model construction and evaluation: The training dataset is classified into the tree algorithm classification, and the model is constructed based on the attribute values of the category. In the evaluation stage, after constructing the model, the testing dataset is used to validate and calculate the accuracy of the constructed model.

Table 2: Criteria for selecting accelerators campaign attributes

Feature	Inf. gain	Gain Ratio	Gini	ANOVA	Chi2
Updates	0.6637801	0.3324233	0.3194444	32.212988	29.76087
The Number of Photos on Updated	0.5454679	0.2734076	0.2896368	14.166566	28.8
The Number of Answers	0.4120948	0.2189206	0.2064957	8.031667	29.257143
The First Update After Launch (day)	0.372378	0.194018	0.1945223	47.562019	11.792453
The Average of Facebook's Fans	0.2410387	0.120589	0.1230769	6.3451249	9.8
The Number of Previous Posts Facebook	0.2353115	0.1785813	0.1468769	19.361167	9.7560976
The Number of FAQ	0.2194413	0.1622182	0.0952381	7.4718196	18.5
Duration (day)	0.1780209	0.1143596	0.1035948	23.17139	2.8138298
The Number of Campaign's Picture	0.1706284	0.0855249	0.1040064	11.525504	7.521978
The Number of Rewards Row	0.1422736	0.071552	0.0905474	6.2919257	4.4263158
The Number of Video on Updated	0.1342244	0.0940237	0.065812	4.0937423	9.6571429
Rewards of Founder's Product	0.1189995	0.0595475	0.0757341	6.0073227	3.7977528
The Number of Campaign's Video	0.0904137	0.0719162	0.0375231	4.1509659	2
The Number of Funded Campaigns	0.078768	0.041111	0.0453838	3.215439	4.4642857
The Number of Youtube's Video	0.067795	0.0409251	0.028125	2.4938756	3.923913
Goal	0.067365	0.0337096	0.0400794	2.9009926	0.9494382
Youtube's Subscribe	0.0470881	0.0266875	0.0252091	0.6110471	3.3898305
Limited Rewards of Founder's Product	0.046544	0.0234078	0.0281618	3.6689214	2.45
The Number of Previous Youtube's Video	0.0378485	0.0198812	0.022899	1.1594023	1.2071429
Lowest Price of Founder's Product	0.0264917	0.0135737	0.0167388	0.0612519	1.8291139
Rewards of Others Product	0.0263919	0.0149797	0.0168229	1.421655	0.5319149
Estimated Delivery (day)	0.0030081	0.0015195	0.0018379	2.2764253	0.0240964

4.4.3 Evaluation

Evaluation of data mining results: In this stage, other results of logistic regression techniques, random forest method, support vector machine, AdaBoost, and Bayesian network method are compared and evaluated with the results obtained from the data mining decision tree method. In this stage, the analyses required for validating the model and its efficiency are presented. Evaluation is done using Cross Validation method by dividing the data into 10 sets, 9 sets of which were training data and one set were related to testing data. This evaluation was repeated 10 times to do it in the best way and examine the average results. The overall structure of the project has been represented in Figure 3 using Orange Software.

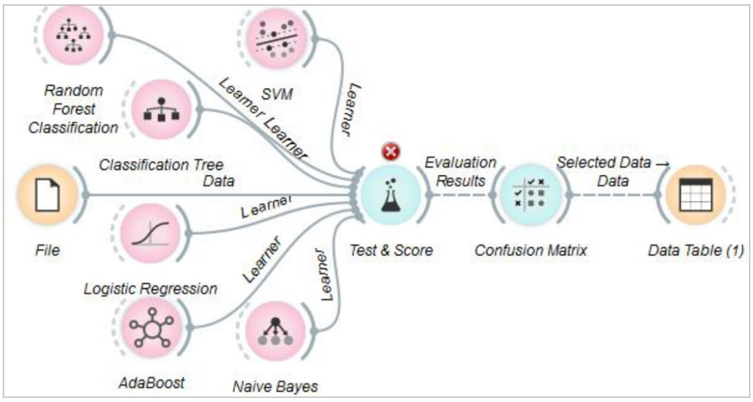

Figure 3: Overall structure of the data mining project in Orange Software

4.5 Initiators' performance in the area of accelerators in different data mining models

The results related to the initiators' performance in the area of accelerators have been presented in Table 3.

The Bayesian classification method and logistic regression with 89.8% accuracy showed the highest accuracy, and the random forest method with 86.7% accuracy, and the decision tree method, support vector machine, and AdaBoost method with 84.4% accuracy respectively were located in the later rankings. Therefore, the decision tree of initiators' performance in the area of accelerators shows the significant accuracy of the model.

Table 3: Initiators' performance in the area of accelerators

Category	Accelerators				
Method	**AUC**	**CA**	**F1**	**Precision**	**Recall**
Logistic Regression	0.900	0.898	0.904	0.899	0.898
Random Forest Learner	0.867	0.867	0.876	0.867	0.867
SVM Learner	0.845	0.844	0.853	0.844	0.844
Classification Tree	0.845	0.844	0.853	0.844	0.844
AdaBoost	0.845	0.844	0.851	0.844	0.844
Naive Bayes	0.898	0.898	0.906	0.899	0.898

4.5.1 Decision tree of initiators' performance in the area of accelerators

Figure 4 represents the decision tree of Initiators' performance in the area of accelerators. The number of YouTube subscribers in the first node of the decision tree represents the highest value of this attribute for division. If the number of YouTube subscribers is higher than 32 members, the initiator's project is more likely to be funded. Otherwise, if the number of initiators' YouTube subscribers is less than 32 members, there is a possibility of funding the initiator's project, provided that the number of answers on the initiator's campaign page is more than 7.

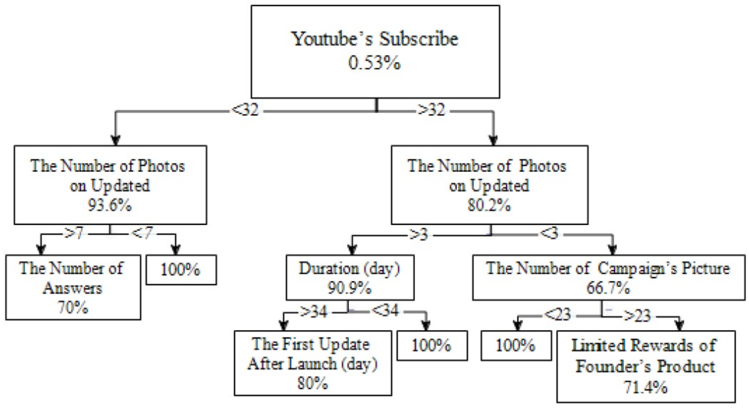

Figure 4: The decision tree of initiators' performance in the area of accelerators

4.5.2 Initiators' performance in the areas of direct investment and growth centers in different data mining models

The results related to the initiators' performance in the area of direct investment and growth centers have been presented in Table 4.

Table 4: Initiators' performance in the areas of direct investment and growth centers

Category	Business incubator					Direct investment				
Method	**AUC**	**CA**	**F1**	**Precision**	**Recall**	**AUC**	**CA**	**F1**	**Precision**	**Recall**
Logistic Regression	0.863	0.867	0.897	0.872	0.867	0.988	0.983	0.987	0.984	0.983
Random Forest Learner	0.912	0.933	0.951	0.934	0.933	0.925	0.933	0.950	0.933	0.933
SVM Learner	0.887	0.900	0.925	0.900	0.900	0.887	0.883	0.909	0.892	0.883
Classification Tree	0.925	0.917	0.935	0.924	0.917	0.875	0.867	0.895	0.880	0.867
AdaBoost	0.875	0.883	0.911	0.885	0.883	0.912	0.917	0.937	0.918	0.917
Naive Bayes	0.975	0.983	0.988	0.984	0.983	0.975	0.983	0.988	0.984	0.983

In the area of the stock exchange market, the Bayesian classification method with 98.3% accuracy showed the highest accuracy, the random forest method with 93.3% accuracy, the decision tree method with 91.7% accuracy, the support vector machine with 90% accuracy, AdaBoost method with 88.3% accuracy, and logistic regression with 86.7% accuracy respectively were located in the later rankings. In the area of growth centers, the Bayesian classification and logistic regression methods with 98.3% accuracy showed the highest accuracy, and the random forest method with 93.3% accuracy, the AdaBoost method with 91.7% accuracy, support vector machine with 88.3% accuracy, and decision tree method with 86.7% accuracy were located in the next rankings.

4.5.3 Decision tree of initiators' performance in the area of accelerators

The results of the decision tree obtained based on the initiators' performance in the area of accelerators shown in Figure 5 indicate that "The number of updates" during the project period is of special importance, and if it is higher than zero, the probability of project to be funded is increased 100%. In this stage, if the "number of previous posts on Facebook before starting the campaign is higher than 19 posts, the project will be funded.

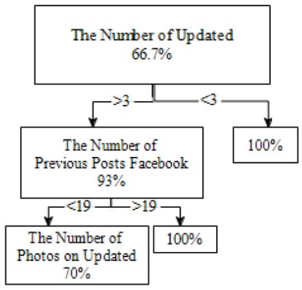

Figure 5: Decision tree of initiators' performance in the area of accelerators

4.5.4 Decision tree of initiators' performance in the area of growth centers

The decision tree of initiators' performance in the area of growth centers has been presented in Figure 6. Examining the decision tree reveals the significance of "the number of answers to people during the campaign period" in this area. If it is higher than zero, it will increase by 95%, and if it is zero, the target amount will be of special importance in funding the project.

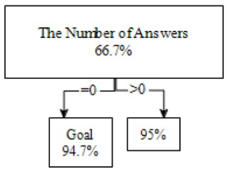

Figure 6: Decision tree of initiators' performance in the area of growth centers

4.6 Potential sponsors' feedback

In this stage, the attributes of potential sponsors' feedback to the initiator's activities on the Facebook and YouTube social networks during the campaign period were examined and the most important effective factors were identified. The dataset includes 130 campaigns in the area of accelerators, 60 campaigns in the area of direct investment, and 60 campaigns in the area of growth centers. Of the total 48 attributes, 20 cases are related to the initiators' performance.

4.7 Descriptive findings

The summary of descriptive statistics related to the potential sponsors' feedback in the areas of accelerators and direct investment has been presented in Table 5. The results confirm the validity of all numerical values.

4.8 Data analysis and model evaluation

4.8.1 Potential sponsors' feedback in the areas of accelerators and direct investment in different data mining models

The potential sponsors' feedback in the areas of accelerators and direct investment in different data mining models has been shown in Table 6.

In the area of accelerators, the support vector machine with 85% accuracy showed the highest accuracy; further, the decision tree and AdaBoost methods with 83% accuracy, the Bayesian method and random forest method with 81% accuracy, and the logistic regression method with 79% accuracy respectively were located in the next rankings. Therefore, the decision tree of potential sponsors' feedback enjoys a higher accuracy in the area of the gold market. In

Table 5: Descriptive statistics of potential sponsors' feedback in the areas of accelerators and direct investment

Category	Accelerators				Direct investment			
Feature	Min	Max	Mean	std.dev	Min	Max	Mean	std.dev
The Number of Facebook Likes	1	107919	2495.352	10322.65	0	56349	3179.86	9106.306
The Number of Facebook Shares	0	17496	464.453	1849.596	0	4441	331.82	846.823
The Number of Facebook's Positive Comments	0	2425	73.477	262.907	0	3910	128.36	561.155
The Number of Facebook's Total Comments	0	2490	96.25	295.966	0	4064	134.7	583.354
The Number of Facebook's PTAT	2	127905	3056.055	12262.05	0	64854	3646.38	10401.4
The Number Engagement Rate in Facebook	0.02	125.069	19.148	21.97	0	94.11	21.5	24.78
The Number of Positive Sentiment	0.251	167.286	15.6	20.421	0	96.967	19.028	21.969
The Number of Facebook's Reach (Main)	0.019	114.623	16.721	19.726	0	72.671	18.43	21.256
The Number of Facebook's Reach (Sub1)	0	0.971	0.179	0.169	0	1.333	0.172	0.209
The Number of Facebook's Reach (Sub2)	0.5	1.007	0.98	0.048	0	1.036	0.984	0.142
The Number of Youtube's Positive Comments	0	206	8.5	21.623	0	104	3.48	15.147
The Number of Youtube's Total Comments	0	256	12.828	29.387	0	112	3.84	16.364
The Number of Youtube's Views	0	201289	21284.52	36330.07	0	112060	3994.92	16775.27
The Number of Youtube's Likes	0	2315	83.68	230.911	0	6187	142.64	874.676
The Number of Youtube's Engagement Rate	0	1.609	0.174	0.351	0	5.612	0.265	0.872
The Number of Youtube's Reach	0	1	0.423	0.362	0	1	0.16	0.347
Gross Rating Point (GRP) in Facebook (Main)	0.024	171.934	22.308	27.605	0	85.647	21.23	23.364
Gross Rating Point (GRP) in Facebook (Sub1)	0	2.081	0.242	0.271	0	2.619	0.229	0.386
Gross Rating Point (GRP) in Facebook (Sub2)	0.904	2.143	1.341	0.306	0	2.177	1.185	0.365
Gross Rating Point (GRP) in Youtube	0	2.143	0.567	0.524	0	1.107	0.179	0.386

Table 6: Initiators' performance in the areas of direct investment and growth centers

Category	**Direct investment**					**Accelerators**				
Method	**AUC**	**CA**	**F1**	**Precision**	**Recall**	**CA**	**F1**	**Precision**	**AUC**	**Recall**
Logistic Regression	0.786	0.781	0.788	0.783	0.781	0.537	0.617	0.729	0.593	0.617
Random Forest Learner	0.807	0.805	0.815	0.805	0.805	0.688	0.733	0.805	0.728	0.733
SVM Learner	0.850	0.852	0.865	0.853	0.852	0.650	0.767	0.851	0.827	0.767
Classification Tree	0.829	0.828	0.841	0.828	0.828	0.675	0.750	0.828	0.741	0.750
AdaBoost	0.833	0.836	0.849	0.836	0.836	0.675	0.750	0.828	0.741	0.750
Naive Bayes	0.814	0.812	0.824	0.812	0.812	–	–	–	–	–

the area of direct investment, the classification of the support vector machine with 77% accuracy ranks first. Further, the random forest method with 73% accuracy, the decision tree method, the AdaBoost method with 75% accuracy, and the logistic regression method with 62% accuracy were located in the next rankings, respectively. Therefore, the decision tree of potential sponsors' feedback enjoys an acceptable accuracy in the area of accelerators.

4.8.2 Decision tree of potential sponsors' feedback in the area of accelerators

The decision tree of the initiators' performance in the area of the gold market has been presented in Figure 7. The first node of the tree represents the number of times the clip is shown on YouTube (The number of YouTube views), which is of great importance in funding the project. If this number is higher than 5120, the probability of funding is increased. Moreover, if the number of Facebook's total comments is more than 13, the probability of funding will be higher than 97%. Therefore, the first method concentrates more on the number of YouTube views and the total number of comments on Facebook.

But if the number of comments on Facebook is less than 13, the number of YouTube's reach would be of special importance in funding the project. While the number of clip views on YouTube with less than 5120 nodes is the feedback rate on YouTube if it is less than 0.118, the project would be funded with a probability of 96%. Otherwise, the number of Facebook's reach would be of great significance.

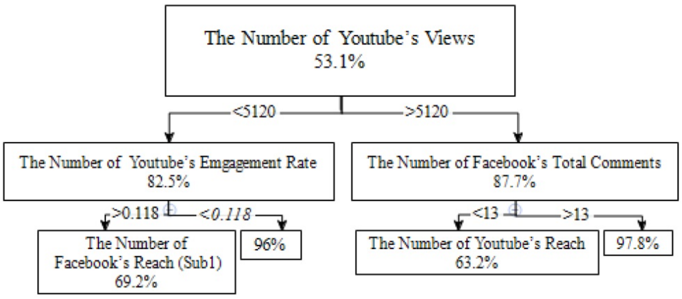

Figure 7: Decision tree of potential sponsors' feedback in the area of accelerators

4.8.3 Decision tree of potential sponsors' feedback in the area of accelerators

The decision tree of the potential sponsors' feedback in the area of accelerators represented in Figure 8 indicates that the first and the most important node is related to the number of likes on Facebook during the campaign period. If it is less than 55, the project would not be funded. Further, if it is greater than 55, the GRP on Facebook and the number of Facebook's Positive sentiments would be effective in funding the project.

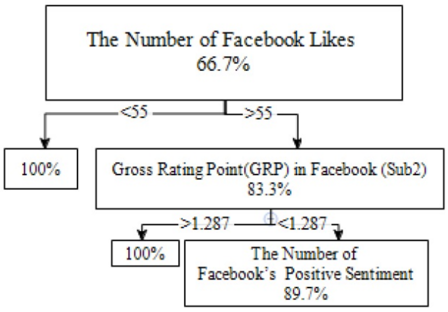

Figure 8: Decision tree of potential sponsors' feedback in the area of accelerators

5 Discussion and conclusion

Despite the increasing development of crowdfunding platforms especially reward-based crowdfunding in knowledge-based companies, a success rate of less than 50% is observed. For this reason, identifying strategies to increase the success rate of crowdfunding as well as formulating models with high predictive accuracy would play a significant role in this success. In this research, an appropriate model has been presented for the first time in the case of the success of reward-based crowdfunding. The factors affecting successful crowdfunding have been obtained using attributes extracted from the data of successful and unsuccessful campaigns of domestic websites in the interval of January 2019 to January 2022. Furthermore, some models have been presented for investigating successful crowdfunding by the use of tree structure of data mining technique due to its high capability in classification and prediction in three areas of accelerators, direct investment, and growth centers. In addition, the potential sponsors' feedback on the initiator's activities on the Facebook and YouTube social networks during the campaign period were examined in the campaign fund rate and the effective factors were presented using the tree structure. The proposed model allows the initiators of innovative ideas as well as small- and medium-sized businesses to attract potential sponsors and increase their success rate. Undoubtedly, there is risk and failure in every creativity and innovation. We hope that the model proposed in this research can reduce the percentage of campaign failure and risk related to initiators.

The results reveal that in the case of initiators' performance, decision tree structures with 85% accuracy in the area of accelerators with effective factors, the number of YouTube subscribers, the number of photos on the updated page during the campaign period, and the number of photos on the campaign page with 92% accuracy in the area of direct investment with effective factors, the number of updates during the campaign period, the number of posts on Facebook before launching the campaign with 87% accuracy in the area of growth centers with effective factors, and the number of answers to individuals during the campaign period are appropriate models.

Moreover, in the case of potential sponsors' feedback, the decision tree structures with 83% accuracy in the area of accelerators, the number of times the clip view on YouTube, the total number of comments on Facebook, the reach rate on YouTube, feedback rate on YouTube, secondary reach rate on Facebook with 75% accuracy in the area of direct investment with effective factors, number of likes on Facebook, GRP on Facebook (sub-2), positive feeling on Facebook are considered appropriate models.

In the end, future researchers are proposed to study the followings:

- Investigating all the classifications (capital market) of the domestic crowdfunding websites using the proposed method as well as other data mining techniques in predicting the funding rate.
- Investigating the Indiegogo crowdfunding website using the proposed method and comparing it with the domestic websites
- Investigating large Asian crowdfunding websites, especially in China, such as Demohour, AngelCrunch, DreamMore Fundactor, MasseyKid, CT Quan, and Zhang Chu using the proposed model and comparing it with large crowdfunding websites in the United States

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