Modelling Approaches for Lending Based Crowdfunding : A Systematic Survey

Arvind Srinivasan, Akilandeswari P

Abstract—The exponential growth and ubiquity of the Internet since its advent have led emerging entrepreneurs to seek new avenues of financial support for funding their innovations. Evolved as an alternative source of finance for growing businesses, Crowdfunding democratises venture capitalism by providing benefits to patrons by offering them incentives such as products, rights or equity. Although there exist apparent benefits for a backer if a deal succeeds, there is a risk of failure due to information asymmetry or other factors. Researchers have proposed many qualitative and quantitative strategies to explore and mitigate these factors. From over 50 papers offering a brief overview on the discovery of these factors through qualitative analysis, this paper correlating with the latest trends in modelling approaches, for both prediction and exploration of lending-based crowdfunding mechanisms. Graphical Analysis of surveyed literature is used to support the inference, concluding with a discussion on promising future research directions.

Index Terms—Literature survey, Crowdfunding, Decision Making, Risk Analysis, Deep Learning, Predictive Methods.

1 Introduction

CROWDFUNDING refers to the practice where individuals with innovative, lucrative ideas showcase them to canvass the audience for financial support in exchange for benefits once the project is ready to hit the market. This method of alternative funding is extremely valuable to those that lack the necessary financial backing to navigate across the fiscal roadblocks that tend to hamper the growth of a project, usually during its incubation period – referred to as the early-stage funding gap [1]. In recent years, online platforms such as IndieGoGo, Rocket Hub and Kickstarter have become increasingly popular, facilitating the growth of this mode of alternative finance. Notably, according to Kickstarter, 4.7 billion US Dollars have been pledged for funding projects since its establishment in 2009. Yet, only 37.49% of those projects have seen the light of day [2]. Probable reasons for this discrepancy might be a general lack of trust, that arise due to the anonymous nature of e-commerce systems causing *information asymmetry* [3]. Thus it is imperative to find better methods to accurately assess potential risks and rewards so that creators and investors alike can glean in on the various factors that determine a campaign's success and funding potential respectively. Throughout the years, several qualitative and quantitative approaches have been applied to discover trends, draft guidelines and propose predictive methods for enabling successful crowdfunding campaigns.

This paper tries to provide a holistic overview on the qualitative aspects of past research and its inferences on various contributing factors for success. Through these theoretical insights, different predictive and explorative modelling strategies proposed to approach the problem of risk analysis and success prediction are explored. This literature survey is structured to discover and present correlations between these discovered factors and the proposed modelling approaches. All surveys are segregated based on the types, stakeholders, life-cycle and success factor for a crowdfunding campaign. The findings from this survey are then graphically analysed to discover gaps in research and discuss potential for future research within the domain of modelling mechanisms.

- *Arvind S. is an undergraduate student, pursuing Bachelor of Technology in Computer Science and Engineering at SRM Institute of Science and Technology.*
  E-mail: arvind@cheenu.net
- *Akilandeswari P. is with the Department of Computer Science and Engineering, SRM Institute of Science and Technology, Kattankulathur, Chennai TN, 600091 India.*
  E-mail: (see https://www.srmist.edu.in/faculty/p-akilandeswari).

2 Overview of Crowdfunding

The following sections provide a summary on the different terminologies in crowdfunding research found in literature, with respect to the focus of this paper.

2.1 Types of Crowdfunding under Focus

Based of the reward-based paradigm and commonly referred to as *Peer to Business (P2B)* crowdfunding, they act either as a *traditional* loan, repaid with interest regardless of success or as a *forgivable* loan [4] where repayment is based on profitability. These forgivable loans can be further classified based on the degree of benefits in return for funding, as follows.

2.1.1 Donation-Based

Campaigns launched by charity and non-profit organisations belong to this category. They only offer intangible rewards such as tokens or recognition [5]. These pro-social campaigns usually elicit guilt of not giving to evoke emotion-driven decision making through linguistic narratives [6], [7]. *Gofundme* is an example of a platform that predominantly hosts donation-based campaigns [8].

2.1.2 Reward-Based

A dominant crowdfunding model [9], these campaigns focus on offering incentives for funding a project which may include offers, deals or discounts. These campaigns can be distinguished into *All-Or-Nothing (AON)* Model and *Keep-It-All (KIA)* Model based on the entrepreneurial responsibility [10] where the latter might overlap into the forgivable loan model in P2B Crowdfunding. *Kickstarter* is a popular platform that follows the AON model for reward based crowdfunding [2].

2.2 Crowdfunding Stakeholders

2.2.1 Founders

Also referred as Fundraisers or Creators, these are the campaigners that try to elicit funds for their projects. Entrepreneurial risks are important obstacles to overcome [11] for this group of people since delivering on promises would secure the reputation for future prospects.

2.2.2 Funders

Alternatively known as Investors or Backers, this refers to the "crowd" that funds a project of their liking. Investment Risks are crucial for them especially when dealing with Reward Based and Lending Based Campaigns. They need to be accurate judges of a project's potential before its inception.

2.2.3 Intermediates

Commonly referred to as platforms, they may be platforms or agencies acting as the interface between creators and backers. Crucial concerns for this group includes Project Boosting, pruning Bogus Projects, tracking Undelivered Projects and banning users involved in unethical practices [12] without compromising the platform's integrity to both participating parties.

2.3 Life-cycle of a Crowdfunding Campaign

2.3.1 Pre-launch Phase

This part of the life-cycle focuses on aspects of Market Research, Campaign Planning and Actionable Deliverables. This phase plays a significant role in selecting the optimal funding selection and pricing plan for a campaign as they depend on a stochastic market driven by necessary investments and latest trends [13]. This phase prioritises effective content design before launching the campaign.

2.3.2 Post-launch Phase

Referred as the 'Growth' Phase, after a campaign's launch, this phase is a vital period for a project to accumulate and gather funding while expanding on their goals and preparing for delivering the promised rewards. Statistics [2] have shown that a large number of emerging, live projects are either being cancelled or suspended before reaching the funding goal. Continuous updates on project milestones are found to help in increasing the trust and belief of backer in the campaign.

2.3.3 Post-funding Phase

This is the final but the most important phase of a project's life-cycle after funding period ends. The main focus of this phase is to have continuous and consistent engagement with the backers of the projects to follow through on the delivery of rewards. Dissatisfaction during this phase can backfire on reputation of the campaign's creators.

3 SURVEY METHODOLOGY

To carry out this survey on scientific literature, 52 articles were retrieved by using the search terms: *"Crowdfunding"*, *"Success"*, *"Campaign"*, *"Prediction"* and similar such keywords in Google Scholar and in reputed Journals. Of these 52, 20 articles focused on proposed Economic Models for Crowdfunding which is briefly touched upon to explore insights into various factors that affect crowdfunding. The remaining 32 articles that focus on different modelling approaches is elaborated in this survey with sufficient detail.

Figure 1 showcases the top 20 keywords in the chosen papers, ordered by frequency. From these keywords, we can infer the following conclusions:

- Most of the research on Reward-Based Crowdfunding use Kickstarter as the benchmark due to its popularity and widespread community.
- Most Modelling Approaches are Predictive - focused on building recommender systems through quantitative analysis of text, social and platform-related metrics.

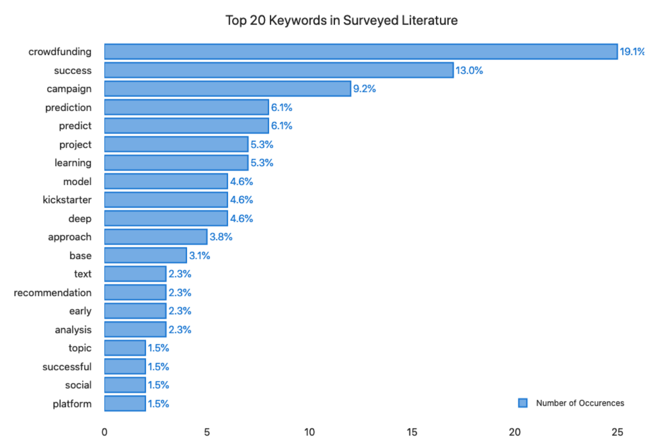

Fig. 1. The frequency of Top 20 Keywords in the chosen papers for Survey, ordered by most frequent first.

The eligibility criteria for this survey mainly involves Journal Articles and Conference Proceedings while allowing for Book Sections and Official Reports in any form (online or offline), except for manuscripts on graduate thesis (See 3.4.4). This survey is organised to explore the trends regarding the mathematical and algorithmic concepts used in these modelling approaches by correlating them with contributing factors to success as elaborated in Section 3.3, with inferences being supported and accompanied by Graphical Analysis of the surveyed literature.

3.1 Existing Survey on Literature

Research on Crowdfunding is multi-faceted, multi-disciplinary and has multiple objectives of focus. The objectives examined in earlier literature surveys were organised either based on the stakeholders(2.2) [30] or based on the or the types(2.1) [31]. In these surveys, Legal, Quantitative and Qualitative Aspects of Crowdfunding

Ref. No.	Authors	Concept	Issues Identified	Possible Enhancements
[14]	R.S and R.K (2016)	Classification model for the analysis of Kickstarter campaigns by using direct and dependent information.	• Dependent Information extracted in Post-Funding Phase of Campaigns.	• Analysis of Textual Content for predicting Pre-Launch Phase
[15]	Yuan et. al. (2016)	Using DC-LDA Framework to extract semantic meaning from project descriptions to predict funding success.	• LDA necessitates choosing of optimal number of topics prior training.	• Hierarchical Dirchlet Process Framework can be used for automatically evaluating the optimal number of Topics.
[16]	Kaur and Gera (2017)	Using Founder Connectivity in Social Media Platforms (Twitter) as a predictor for campaign's success.	• The research focuses on the count but not on the sentiments in tweet content.	• Sentiment Analysis in conjunction with this research can provide a more complete picture.
[17]	Lai et. al. (2017)	Mining features from Funder Comments and Founder Updates for improved accuracy in prediction of Crowdfunding Campaigns.	• Lack of Semantic Analysis on the textual content.	• Corpus for Sentiments can be made category-specific to improve accuracy.
[18]	Wang et. al. (2017)	Sentiment Analysis of Campaign Title, Blurb and Description to support Crowdfunding Campaign prediction.	• Focus is limited to sentiments in textual data.	• Image Classification can be used to explore effects of visual cues.
[19]	Lee et. al. (2018)	Extracting Linguistic cues along with project, creator and multimedia information for success prediction.	• Multimedia information focuses on the count but not on the content itself. • Creator Information does not factor creation history.	• Image Classification can be used to explore effects of visual cues. • Creator Experience can be computed to support prediction.
[20]	Zhao et. al. (2019)	Study on Donation Recurrence and Donor Retention with behavioral information to predict using Joint Deep Survival Model (JDS).	• The model does not capture prolonged sequence dependent events.	• Extended sequence can be modelled by means of a Moving Time Window.
[21]	Tan et. al. (2019)	Modelling Competing Charge-off and Pre-payment Risks for P2P Lending Platforms using Deep Learning.	• Variable Payment Schemes are not modelled by this research.	• Explore Loan State Path to model transition probability to counteract this issue.
[22]	Salahaldin et. al. (2019)	Utilise Dynamic Programming to model crowdfunding success with regards to Target and Utility of project.	• Works only on crowdfunding mechanisms that lack a hard limit on maximum investment.	• Can factor temporal degradation of Investability of a project.
[23]	Koch and Siering (2019)	Exploring success factors and their interrelations via. Decision and Signalling Theory.	• Lack of a predictive implementation of this explorative model.	• Can utilise Machine Learning to implement this model. • Image Classification can be used to explore effects of visual cues.
[24]	Kaminski and Hopp (2019)	Neural network and NLP-Based approach to predict the results of crowdfunding pitches by exploring Multimedia Content.	• Focus is limited only to the Technology and Design Category. • Conclusions cannot be extrapolated to other categories with different needs and wants.	• By collecting and analysing multimedia information across all categories, a better picture can be obtained on this scenario.
[25]	Wang et. al. (2019)	Combines time-series and time-invariant features for Short-term Post Launch Predictions of success in Medical Crowdfunding.	• Time-varying features cannot be generalised to flexible goal systems that allow extension of funding period and do not factor platform boosting.	• Exploring Reciprocal Engagement Behaviour through temporal analysis.
[26]	Kindler et. al. (2019)	Exploring the influence of early pledging and virality towards success of crowdfunding campaigns by probablistic model.	• The support for homophily hypothesis does not factor social connectedness between funders and founders.	• A more authoritative result would involve social networking with the model for virality.
[27]	Wu et. al. (2019)	Exploring market competition for modelling funding success using a Graph Based Market Environment Model.	• The optimal pruning parameter estimation for the Graphical Attention Network is not explored.	• Optimal Pruning Estimator for the proposed model can be addressed.
[28]	Shafqat and Byun (2019)	Language modeling based neural network to predict discussion trends and provide recommendations using Deep Learning Model.	• Profile Features of Founders are not considered. • Limited Linguistic Features explored.	• Part Of Speech Tagging can be used to extract pronouns, adjectives to explore a range of emotions for more expressiveness.
[29]	Wang et. al. (2019)	Reinforcement Learning Approach through Actor-Critic Framework for tracking dynamics of Crowdfunding.	• The average daily distribution ratio does not factor fluctuations in funder enticement.	• Resolve the same by incorporation of funder distribution across the funding period.

TABLE 2.3.3 • The above table lists the journal papers that have been recently published along with the issues discovered with proposal of methods to mitigate them.

have been explored in-depth, but the focus was confined within the field of economics. Moreover, Business models supporting the process of crowdfunding have also been analysed based on the business, financial and material motivations have also been explored in detail [32]. Currently, there is a lack of extensive literature on empirical research in the domain of Crowdfunding, focusing on the different modelling approaches. The following survey attempts to bridge this gap.

3.2 Issues in Existing Literature

Exploring existing research literature with respect to modelling techniques, Table 2.3.3 elaborates on the Journal Papers collected regarding this field, briefing on the concepts proposed along with the issues identified, to discover gaps in research. As a personal contribution, the table also proposes possible enhancements to the existing proposed solutions, paving way for further exploration into this field.

From table 2.3.3, we can find that, across the years, the focus for predictive and explorative modelling for crowdfunding has slowly shifted from Machine Learning techniques to more Graphical, Probabilistic Methods that involve Deep Learning. During this period, we also find a gradual progression towards the discovery and implications of hidden metrics (either linear or non-linear) through new, innovative analysis methods. However, during this survey we discovered that inferred factors that contribute to a campaign's success don't vary. These factors can be broadly classified into three contributors, as elaborated in section 3.3.

3.3 Crowdfunding Success Factors

Most economical literature agree that the success of a crowdfunding campaign depends broadly on factors namely Media Richness and Transparency, Founder Networks and Experience and Investor Engagement. These factors of success, along with the exploration of corresponding economic models, are developed in the following sections.

3.3.1 Clear Content with Rich Multimedia

Project founders during the design of a campaign distribute project related information through detailed descriptions and additional imagery. *Perceived diagnosticity*, the theory that examines the use of descriptive content in influencing judgments, suggests that positive effects are directly proportional to the meaningfulness of information [33]. However, to enable the investors to retain the conveyed information while mollifying their apprehension concerning the project, it is necessary to introduce multimedia (images and video) content. Studies have shown significant improvements to the retention of user attention in websites, particularly in those designed for e-commerce that utilise multimedia to create an illusion of credibility [34], [35].

Moreover, according to Media Richness Theory [36], the use of textual descriptions with corresponding graphical accompaniment increases the chances for successful funding of a project. However, richness in the media alone cannot ensure funding since the clarity and transparency of related content are also vital in enticing investors since it gives a feeling of trust and credibility - an intrinsic social motivation for donors to support a project [37]. At the same time, the problem of information insufficiency [9], the misrepresentation or failure to disclose relevant facts about the projects and creator [38], is also resolved.

3.3.2 Founder Networks and Experience

Networking is fundamental in ensuring that a project has a broad reach on the targeted audience. Studies have shown that increased networking boosts the chances of successful funding [9]. In the case of crowdfunding, the number of friendship ties and signals of relational investment are reasonable estimates of network influence [39]. With the appearance of social marketing enabling concurrent promotion from multiple social media outlets [40] via. networking tools, increasing one's reach and hence increasing one's chances of success, has become more convenient than ever before.

Consequently, the pressure on a founder to deliver increases as provability improves, thus reducing the potential for information asymmetry [3].

However, networking alone is inadequate since there is a need to assert the legitimacy of the founder, be it an individual or an organisation, as they act as an indicator of inherent fraud. Investors, who might not have complete information on a founder, tend to reference records of earlier performance due to inherent distrust in their use of funds [11].

3.3.3 Investor Engagement

Studies on investor behaviour suggest two principal determinants of funding and engagement, namely *reciprocity* and *homophily*. Reciprocity, which refers to the tendency for founders to support each other's projects for their mutual success, is found to be more influential than Homophily, which relates to the sharing of similar preferences and interests [41]. Besides, most of the phrases found in campaign content, including comments in successful crowdfunding campaigns, are found to represent reciprocal behaviour [42].

Furthermore, the narrative legitimacy in the context above might derive more information from creator-backer interactions in an online platform community than from solely the visual pitch [43], [44]. Consistent updates on new rewards and social promotion, irrespective of the time of posting, are found to be more substantial than other project parameters as a contributing factor to success [45]. In particular, offering tangible, yet meaningful rewards plays a key role in retaining the existing backer-base while attracting new investors to fund for the campaign [5], [46].

3.4 Organisation of Literature Survey

As diagrammatically represented in the Sunburst Chart (See Fig. 2), the surveyed literature is categorised into five levels of nested complexity namely, *Modelling Type*, *Modelling Approach*, *Type of P2P Lending*, *Paper Type* and *Publication Year*.

3.4.1 Modelling Type

This level of categorisation segregates the modelling approaches into two sub-categories based on the use-case as *Predictive Modelling* and *Exploratory Modelling*. While *Explorative* focuses on modelling for qualitative discovery of factors, *Predictive* focuses on modelling these factors to build recommendation models for stakeholders. From the figure (Fig. 2), we can infer that over 78% (25 papers) of surveyed literature focus on Predictive Modelling while the other 22% (7 papers) focus on Explorative Modelling. This implies that modelling approaches are more commonly used when more focus is given to the resultant interaction between various factors than the contributing factors themselves.

3.4.2 Modelling Approach

The second level of categorisation divides the papers into three sub-categories based on the approaches used namely *Machine Learning Methods*, *Deep Learning Methods* and *Other Methods*.

MACHINE LEARNING METHODS

Approximately, 56% of Predictive and 71% of Explorative types of modelling use Machine Learning Methods. In the former, they are either used as baselines (ex., [47], [48]) for testing prediction or as a combination / modification of existing Machine Learning methods (ex., [14], [49]). In the latter, they are used as supportive techniques to quantitatively assist the exploratory analysis methods. Among the latter, *Logistic Regression* is the most commonly used method for this purpose.

DEEP LEARNING METHODS

From the surveyed literature, it is found that unlike Machine Learning, Deep Learning Methods are used exclusively for Predictive Modelling. Moreover, among the Predictive Modelling approaches, 36% (9 papers) use Deep Learning.

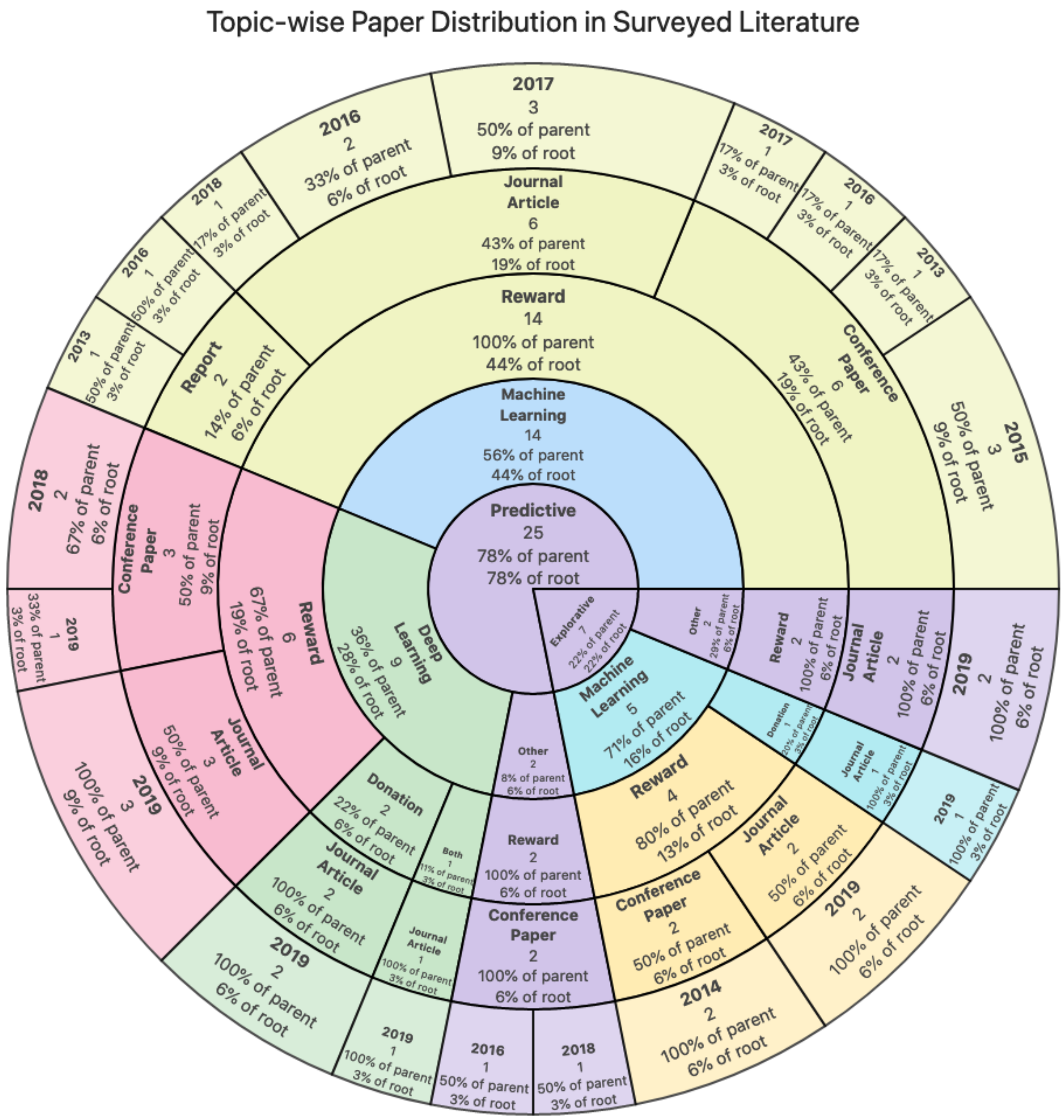

Fig. 2. Topic-wise Paper Distribution among Surveyed Literature across the years 2013 to 2019.

OTHER METHODS

Around 8% of the Predictive and 29% of the Explorative type of modelling use approaches other than Machine Learning and Deep Learning. These include methods such as Graphical Modelling (ex., [27]) and Probabilistic Modelling (ex., [22], [50], [51]). On the whole, 16% (8 papers) apply these techniques either for qualitative and quantitative analysis or for assistance in deriving metrics for predictive and explorative modelling.

3.4.3 *Type of P2P Lending*

As previously described in Section 2.1, the Peer-to-Peer Lending mechanisms are classified into *Reward-Based* and *Donation-Based* sub-categories. As Figure 2 suggests, 88% of surveyed literature focus predominantly on Reward Based Crowdfunding irrespective of the type of predictive approaches while, of the remaining 22% (4 papers), 3 papers focus on Donation Based Crowdfunding and only one paper focuses on both.

3.4.4 *Paper Type*

Based on the mode of publication, these papers are further classified into *Journal Article*, *Report* and *Conference Paper*. Figure 2 shows that, the paper distribution between *Journal Article* and *Conference Paper* is balanced, but only with respect to Reward Based Crowdfunding. Donation Based

Crowdfunding, on the other hand, does not have any conference papers published under its domain. Possible reasons include lack of authoritative research in this aspect.

3.4.5 Publication Year

The deepest level of categorisation is based on the year-wise distribution of the topics discussed above across the years 2013 to 2019. The year 2014 was the only year when exploratory analysis of crowdfunding factors were conducted. Inferring from the Figure 2, based on the recent trend, deeper exploration into this field of crowdfunding research began from 2016, where the focus of predictive modelling approaches shifted away from Machine Learning, beginning with a paper that described the predictive capability of Neural Networks over other supervised Machine Learning approaches [14]. This trend reached its apex at 2019, where the focus shifted from predictive modelling back to exploratory modelling. For analysing these trends in greater detail, Graphical analysis of the surveyed literature is conducted along with the corresponding features and inferred results are elaborated in Section 4.

4 Graphical Analysis

4.1 Stakeholder Focus

As previously described in Section 2.2, the stakeholders focused are *Founder*, *Funder* and *Platform*, which may occasionally overlap over each other. The stakeholders are assigned based on Explicit statements or Implicit information. For instance, Recommendation Tools, unless explicitly specified, can be assumed to be focusing on the Platform. From figure 3, we can see that there is an equilibrium

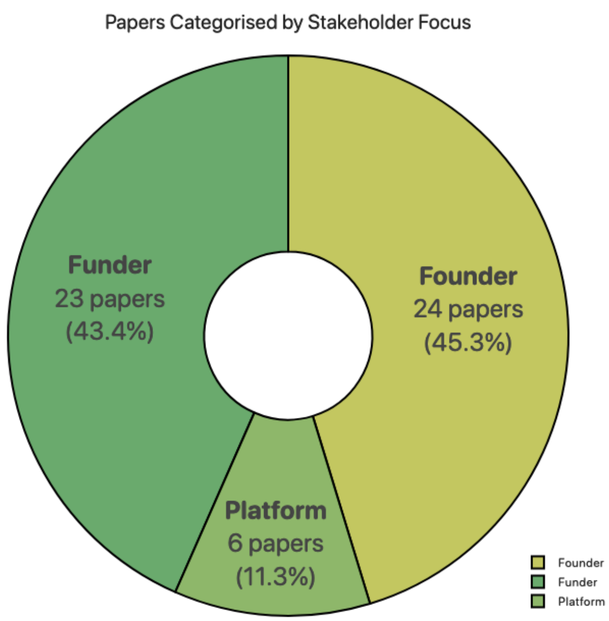

Fig. 3. A Pie Chart describing the distribution of Stakeholder Focus in Surveyed Literature.

between the focus given to Funders (43.4%) and Founders (45.3%). Moreover, since the focus platform-based recommendation models were a recent addition in the last couple of years, the number of papers published for this domain of stakeholders is less, though extrapolating current trends suggest a possible growth in exploration.

4.2 Phases of Crowdfunding Life-cycle

Described earlier in Section 2.3, the phases in the life-cycle of a crowdfunding campaign are *Pre Launch* phase, *Post Launch* phase and *Post Funding* phase, the focus of which may occasionally overlap over each other. For this survey, the papers are categorised based on explicit and implicit information. Explicit information constitutes research hypothesis and conclusions addressed by the authors while Implicit information focuses on the data required for analytical methods used in data processing and information retrieval stages. For instance, papers that apply temporal analysis need time-series information for performing the same. Since temporal information regarding a campaign can only be obtained Post Launch of a campaign, the respective paper is categorised as so. The figure 4 suggests that greatest

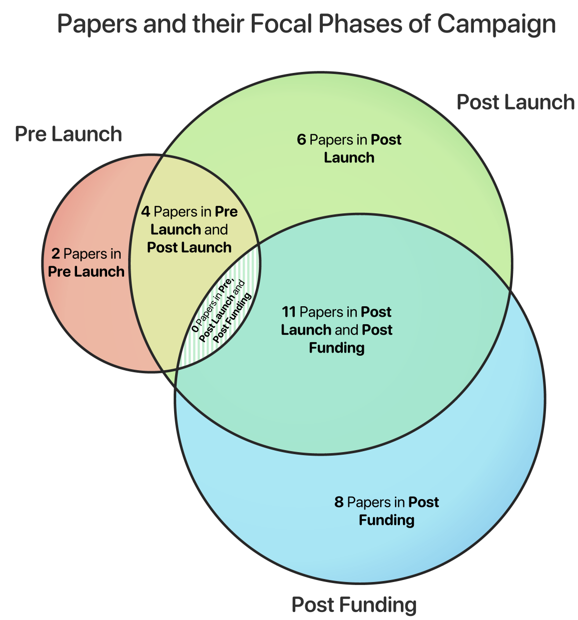

Fig. 4. A Venn Diagram representation of Focus given to various phases of a campaign's life-cycle in Surveyed Literature.

percentage of papers focus on analysis of data retrieved Post Launch and Post Funding, followed by the focus on Post Funding and Post Launch. Pre Launch prediction [52], [53], one of the key milestones necessary for real-time prediction is among the less commonly explored aspect in this domain. Furthermore, this analysis shows that there has not been any predictive or explorative papers published that analyses and models founder and funder behaviour across different stages of the life cycle.

4.3 Focus on Factors of Success

Described earlier in Section 3.3, *Content*,*Networking* and *Engagement* are three key success factors identified whose focus may occasionally overlap over one another. For this survey, the papers are categorised based on explicit and implicit information. Explicit information constitutes addressed research hypotheses and conclusions while Implicit information infers from the interaction between analytical approaches used in the initial stages. For instance, papers that apply social features or graph based analytical models correspond to networking while papers that apply behavioural, survival and competition analysis correspond to Engagement. The figure 5 suggests that greatest percentage

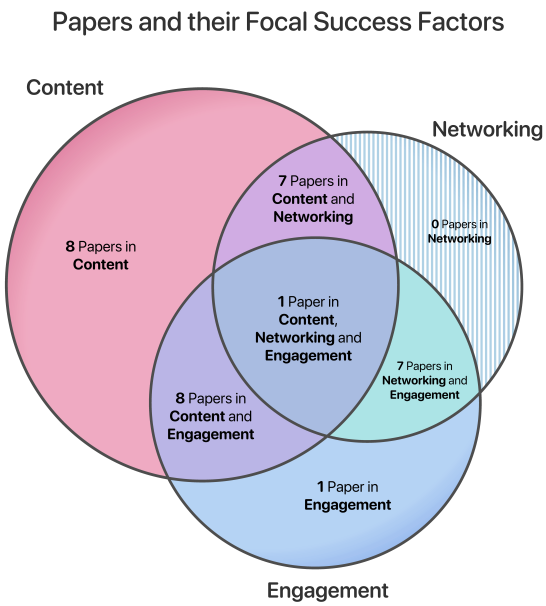

Fig. 5. A Venn Diagram representation of Focus given to various success factors of a campaign in Surveyed Literature.

of papers contribute to Content along with its relationship with Engagement, closely followed by the impacts of Engagement with Content and Networking. There is a noticeable lack of exploratory papers that focus solely on Engagement while no papers are published that predominantly focus on the Networking aspect.

4.4 Feature Exploration

The various features of a crowdfunding campaign that are observed can be broadly classified into seven categories namely *Temporal*, *Social*, *Geographic*, *Static Multimedia*, *Static Textual* and *Static Categorical*, *Static Numeric*.

4.4.1 Temporal Features

These features are used across all years, mainly for temporal analysis. Due to the limitation of Machine Learning, there was a gradual decrease in their implementation until the introduction of Deep Learning since the year 2018. If the projection holds, more papers on temporal analysis would be proposed in the future.

4.4.2 Social Features

Social Features and Temporal features and the most commonly explored features across all the years, with diminishing focus since 2016, which can be attributed to extensive

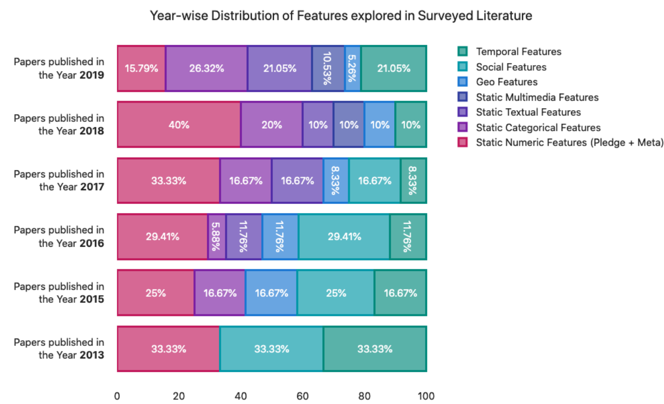

Fig. 6. A Percentage Bar Chart showcasing the distribution of features explored for analysis during modelling for crowdfunding campaigns.

prior exploration. To support this, the chart (Fig. 6) shows that Social features were the most minimally used in the year 2019.

4.4.3 Geographic Features

Geographical features based on location were applied along with introduction of categorical features. Though explored with respect to a narrow domain of Green-funding [54], their general impact on the success of crowdfunding campaigns have not been explored in great detail, though studies based on economic perspective [9] suggest minimal significance.

4.4.4 Static Multimedia Features

The use of multimedia went hand-in-hand with the application of Deep Learning for success prediction, starting from the year 2018. Using Convolutional Networks for Image Classification [25], [53] and Convolutional LSTM Networks for Video Classification, it was possible to use only project content to predict the probability of success with a high degree of accuracy, one of the proposed solutions for Pre Launch Prediction.

4.4.5 Static Textual Features

Commonly used for Linguistic Analysis, the utilisation of text for success prediction was more recent and began in the year 2016 [15], [51], [55]. These Textual Analysis methods applied more complex language modelling approaches such as Topic Modelling following which, Predictive approaches were proposed that utilised Deep Neural Networks for Text classification [56] to aid in success prediction in the years 2018-2019.

4.4.6 Static Categorical Features

Categorical Features form an intersection between the Numeric and the Textual, with exception of the crowdfunding *state* predictor. From the chart (Fig. 6), we find that categorical features were introduced only in 2015, experiencing a gradual increase in adoption except in the year 2018.

4.4.7 Static Numeric Features

From the bar chart (Fig. 6), we can infer that the focus on the numeric features such as Pledge Information and other Project-related Metadata has significantly diminished in the year 2019, thanks to Deep Learning that allows exploration of non-numeric features. The gradual increase in focus between the years 2015 and 2018, indicate an increase in the number of *derived metrics* from visible data. These include application of Natural Language processing techniques such as PartOfSpeech Tagging for extracting words that imply emotion or cognitive process [28].

4.5 Applied Analytical Methodology

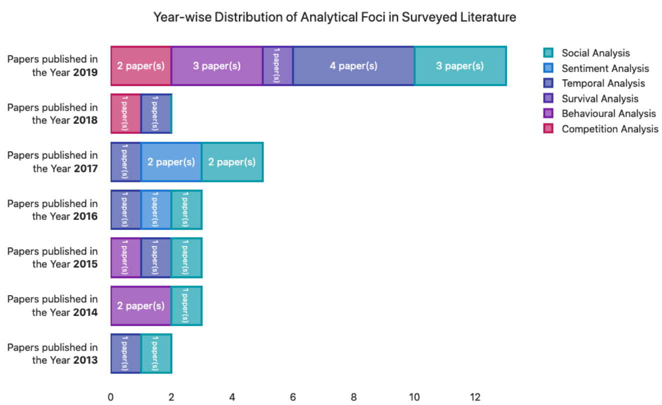

Fig. 7. A Stacked Bar Chart that describes the foci of analysis across the years in surveyed literature.

4.5.1 Social Analysis

As discussed earlier, Social Analysis - the analysis of the impacts of social media connectivity in the success of crowdfunding campaigns - became more extensive as the access to data increased. This can also be correlated with the increase in the number of papers that focused on Networking aspects (3.3). *Derived metrics* and *Graphical Model* [16], [47] were some analytical methods that were applied for the purpose of this analysis.

4.5.2 Sentiment Analysis

Sentiment Analysis - the analysis of emotion behind textual content - focused on Natural Language Processing as a common analytical technique were used for modelling between the years 2016-2017. Comparing the Focus of Analysis (fig. 7) with the analytical methods(fig. 8), we find that during this time, Natural Language processing along with Topic Modelling might have been used for extracting further information from textual data.

4.5.3 Temporal Analysis

Temporal Analysis deals with the temporal features(4.4) such as the variations in pledging behaviour [20], [26] and day-wise pledge per backer distribution [29], to develop models for predicting success of crowdfunding campaigns. As the graph represents, temporal features have always been a primary focus in surveyed literature except for the year 2014 which focused on exploratory analyses. However, this analysis became the most predominant method of analysis in 2019.

4.5.4 Survival Analysis

Survival Analysis is a relatively new analytical technique applied in a recent paper [20] that modelled donor recurrence and donor retention, using temporal metrics with Deep Learning. Survival Analysis can be seen as an intersection between Competition Analysis(4.5.6) and Behavioral Analysis(4.5.5).

4.5.5 Behavioural Analysis

Behavioural analysis includes the study of personality, the psychological tendencies of founders and funders alike [20], [26], [42] in affecting the decision-making regarding funding of a campaign. From the Figure 8, we observe that the trends in behavioural analysis tend to coincide with the Graphical Modelling and Topic Modelling. This implies that Behavioural analysis also has a link with Content and Networking, while utilising this link to discover engagement.

4.5.6 Competition Analysis

Competition Analysis, like Survival Analysis is a recent effort to model competition between different products with their corresponding market environment by filtering them by category to provide recommendations for investors. This Funder-oriented analysis was introduced in the year 2018, with the creation of DMC (Dynamic Market Competition) Model [50], followed by an improvement that incorporated temporal analysis to model competing risks [21], [27]. Apart from this, from Figure 8 we also find that Derived Metrics are commonly followed by Natural Language Processing or Probabilistic Modelling. Moreover, 2019 saw an increase in the application of Probabilistic Modelling Techniques for success prediction of crowdfunding campaigns.

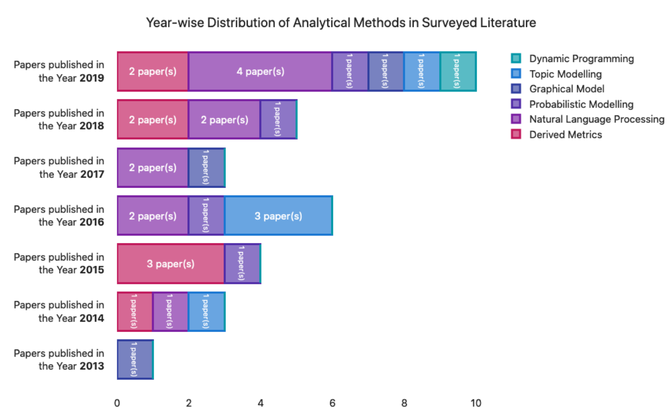

Fig. 8. A Stacked Bar Chart that describes the common methods of analysis applied across the years in surveyed literature.

4.6 Predictive Modelling Approaches

To prevent noise of erroneous results in predictive approaches, Figure 9 shows the most successful of the predictive algorithms identified in the literature. These algorithms include both Machine Learning and Deep Learning Approaches, which will be elaborated in the following subsections.

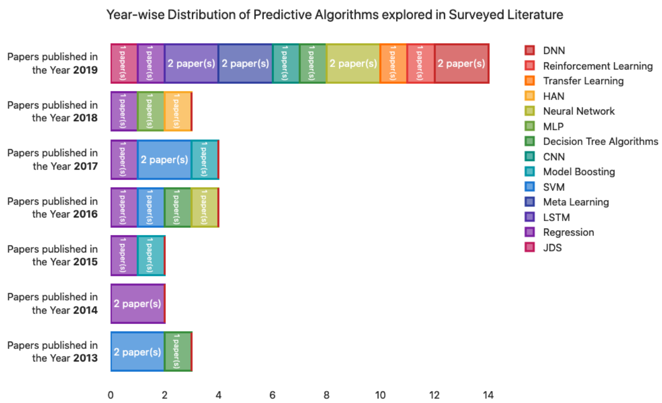

Fig. 9. A Stacked Bar Chart that delineates the various predictive algorithms with the best success rates, used over the years in surveyed literature.

4.6.1 Decision Tree Algorithms

Utilising data on 13,000 projects from Kickstarter, Greenberg et al. derived 13 features to construct prediction engines. Following several prediction models and comparisons with different machine learning algorithms such as Logistic Model Trees, Random Forests, J48 Trees, AdaBoost and SVM, researchers found decision tree algorithms achieved the most desirable result with roughly 68% accuracy. At the same time, SVM only yielded an average accuracy in comparison with the baseline [48].

4.6.2 Support Vector Machine (SVM)

The research focus on leading crowdfunding platforms was the development of methods to predict the success of Kickstarter campaigns. In particular, two predictors frequently observed were money pledged in time-series and social characteristics. Four hours following the launch of a campaign, a combination of both predictors helped improve prediction accuracy by 4%, higher than the 76% accuracy obtained in SVM approach [47].From the linguistic perspective, Chen et al. (2013) trained an SVM model on Kickstarter projects and achieved approximately 90% accuracy with the Android application and Chrome extension employed [57]. Sawhney (2016) showed 92% accuracy in predicting Kickstarter campaigns using linear-kernel SVM [55].

4.6.3 Regression

Combining both classification and censored regression as of survival analysis based, a new approach helps build a sound prediction model which perform in the best rate of 0.8029. The approach delivers a better outcome by employing both successful and failed projects while using both temporal and social network features. Furthermore, improvements can be made on prediction to achieve the best accuracy of 0.9030, if the model includes information on progress a project makes within the first three days after launching [49]. Rakesh et al. (2016) provided a comprehensive regression-based predictive analysis of the work of probabilistic recommendation model, which promotes projects to Kickstarter users by consolidating the dynamic-status of ongoing projects. [51].

4.6.4 Model Boosting

After creating prediction models using, GLM, Random Forest, Gradient Boosting and XGBoost, Lai et al. (2016) demonstrated a maximum accuracy of 96.8% by XGBoost. This accuracy, by far, according to graphical analysis of overall accuracy over the years, is the best possible accuracy [17] attained using Machine Learning Modelling Techniques.

4.6.5 Neural Network

Kamath et al. (2016) reasoned that Neural Networks perform better, reaching up to 94% accuracy in predicting the success of Kickstarter campaigns after building several supervised learning models which include Naïve Bayes, Neural Network, Random Forest and Decision Tree [14].

4.6.6 Reinforcement Learning

Wang et al. (2019) [29] explores a Reinforcement Learning approach for predicting success by utilising an actor-critic framework to create a dynamic pattern switching process that learns termination values from periodic temporal analysis of backer distributions. With increasing rates of accuracy on applying superficial metrics, later papers looked into deep learning for ways to discover and predict new hidden, non-linear parameters.

4.6.7 Deep Neural Networks (DNN)

For modelling potential risks due to prepayment and payoff, a hierarchical grading framework is developed for risk integration and models the graded competing risks using a variation of Multi-Class Deep Neural Networks for feature representation and risks learning [21].

4.6.8 Multi Layer Perceptron (MLP)

By utilising the historical data sets of Kickstarter, Yu et al.(2019) demonstrated an accuracy of 93% by implementing a Multi Layer Perceptron with 2-hidden Re-LU layers with 180 and 80 neurons respectively, optimised by Adam with the loss computed using Binary Cross entropy for binary classification and prediction of successful and failed campaigns [58].

4.6.9 Hierarchical Attention Network (HAN)

Following this, Lee et. al (2018) proposed a Content Based Deep Learning Approach by applying Natural Language Processing to Campaign Content including comments and updates by adopting a Seq2Seq DNN modelled with sentence-level attention using a Hierarchical Attention Model(HAN) to achieve an average accuracy of 90%. Notably, for pre-launch(2.3) campaigns achieves an accuracy of 76% [56].

4.6.10 Convolutional Neural Network (CNN)

Cheng et.al (2019) proposed an approach that leveraged multimedia content without extensive use of meta information. Targeting campaigns at pre-launch(2.3), This method applied BoW Model weighted by TF-IDF transformed into Word Embeddings for textual features while visual features used VGG16 - a Convolutional Neural Net Framework for classification. Only two meta-features: funding goal and category were used in conjunction with this model resulting in an ensemble accuracy of 83% [53]. Furthermore, this paper also incorporates *Transfer Learning* to reduce the training time.

4.6.11 Long Short Term Memory Network (LSTM)

Focusing on an aspect of Donation based Crowdfunding, Wang et al.(2019) uses static variables and time-varying features, with a Long Short-Term Memory(LSTM) Model, the robustness of which, is validated by a timeliness measure to make fast but reliable predictions. The accuracy ranges from 90-95% over a period of 2-4 weeks respectively [59].

4.6.12 Joint Deep Survival Network (JDS)

Zhao et al.(2019) proposed a Joint Deep Survival model(JDS), which can integrate heterogeneous features such as donor motives and social contacts, to jointly model the donation recurrence and donor retention, tested by extensive analysis and validation experiments with large-scale data collected from Kiva [20] with performance exceeding traditional survival frameworks like CDT. For discovery of hidden topics, Latent Dirchlet Allocation (LDA) based Topic Modelling Methodologies have been applied to discover topical information to provide optimised recommendation of campaigns to fund for backers.

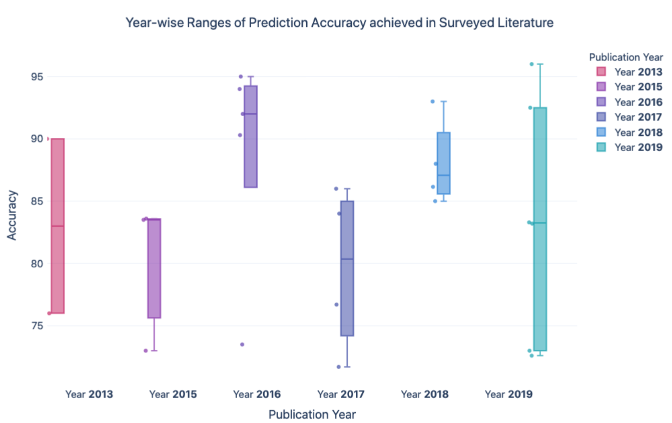

Fig. 10. A Box Plot that describes year-wise ranges in accuracy obtained in surveyed literature.

These are some of the accessible few papers with methods proposed in the domain of predictive approaches for Crowdfunding. As we can observe from the previous section (4.6) and the Figure 10, the range of accuracy varies from 67% to a maximum of 97% approximately. Within this range, the year-wise variations found are the most sparsely for the year 2019 and the most densely for year 2018. However it is to be noted that, though the distribution of accuracy for 2019 is sparse, it does not imply bad modelling practices but rather denotes the exploration using different analytical methods.

5 Conclusion

On reviewing the literature regarding the different modelling approaches and correlating with the respective factors of success identified from the qualitative analyses in economic literature, with support of Graphical Analysis, we arrive at the following conclusions.

- Modelling approaches that focus on the resultant interaction between contributing factors are more common than those that focus on the factors themselves.
- There are no papers on modelling approaches correlating the effects of funder and founder behaviour (pledging or otherwise) with regard to all three phases of a campaign's life cycle.
- The gradual shift of predictive approaches away from Machine Learning has led to the possibility of success prediction during the Pre-Launch Phase.
- Over the years, an increasing trend is observed where more methods of analysis are explored for modelling hidden, previously inaccessible features apart.

These are some of the key conclusions derived from the Graphical Analysis of the survey on Modelling Approaches for Crowdfunding.

6 Future Work

Given the current trend, the future course for modelling approaches in crowdfunding domain would involve real-time analysis with more focus towards pre-launch prediction to facilitate founders. Further research needs to seek and apply concepts in Artificial Intelligence for offering better, smarter recommendations. Hidden empathetic metrics that determine the enticement and motivation of funders towards funding for a campaign needs to be explored further. Current Linguistic analysis approaches such as topic modelling have focused only to project content, comments and updates but the role of rewards are not considered for predictive modelling, which needs to be explored for their predictive contribution. These are some of the identified gaps in this area with proposed directions for future research.

Acknowledgments

The author would like to thank is Mrs. P. Akilandeswari, Senior Associate Professor, Project Guide and Panel Head for Data Miningfor her guidance and support offered throughout the making of this paper.

REFERENCES

[1] Q. Zhang, T. Ye, M. Essaidi, S. Agarwal, V. Liu, and B. T. Loo, "Predicting Startup Crowdfunding Success through Longitudinal Social Engagement Analysis," in *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management - CIKM '17*. Singapore, Singapore: ACM Press, 2017, pp. 1937–1946. [Online]. Available: http://dl.acm.org/citation.cfm?doid=3132847.3132908

[2] "Kickstarter Stats." [Online]. Available: https://www.kickstarter.com/help/stats

[3] M. Lin, N. R. Prabhala, and S. Viswanathan, "Can Social Networks Help Mitigate Information Asymmetry in Online Markets?" *Economics and Information Systems*, p. 16, 2009.

[4] "Crowdfunding," Dec 2016. [Online]. Available: https://ncfacanada.org/crowdfunding/

[5] J. Paschen, "Choose wisely: Crowdfunding through the stages of the startup life cycle," *Business Horizons*, vol. 60, no. 2, pp. 179–188, Mar. 2017. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0007681316301252

[6] T. W. Moss, M. Renko, E. Block, and M. Meyskens, "Funding the story of hybrid ventures: Crowdfunder lending preferences and linguistic hybridity," *Journal of Business Venturing*, vol. 33, no. 5, pp. 643–659, Sep. 2018. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S088390261630338X

[7] S. Agarwal, *Investor's Demographics and Its Impact on Investment Behaviour*. Springer International Publishing, 2017, p. 125–158. [Online]. Available: http://link.springer.com/10.1007/978-3-319-54416-8_6

[8] "What is crowdfunding? campaign basics explained." [Online]. Available: https://www.gofundme.com/c/crowdfunding

[9] E. Mollick, "The dynamics of crowdfunding: An exploratory study," *Journal of Business Venturing*, vol. 29, p. 1–16, 01 2014.

[10] D. J. Cumming, G. Leboeuf, and A. Schwienbacher, "Crowdfunding models: Keep-it-all vs. all-or-nothing," *Financial Management*, vol. n/a, no. n/a. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/fima.12262

[11] E. M. Gerber and J. Hui, "Crowdfunding: Motivations and deterrents for participation," *ACM Transactions on Computer-Human Interaction*, vol. 20, no. 6, pp. 1–32, Dec. 2013. [Online]. Available: http://dl.acm.org/citation.cfm?doid=2562181.2530540

[12] M. Ellman and S. Hurkens, "Fraud tolerance in optimal crowdfunding," *Economics Letters*, vol. 181, pp. 11–16, Aug. 2019. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0165176519301375

[13] F. Xu, X. Guo, G. Xiao, and F. Zhang, "Crowdfunding or bank financing: Effects of market uncertainty and word-of-mouth communication," 2018.

[14] R. Kamath and R. Kamat, "Supervised learning model for kickstarter campaigns with r mining," *International Journal of Information Technology, Modeling and Computing (IJITMC)*, vol. 4, no. 1, pp. 19–30, 2016.

[15] H. Yuan, R. Y. Lau, and W. Xu, "The determinants of crowdfunding success: A semantic text analytics approach," *Decision Support Systems*, vol. 91, pp. 67–76, Nov. 2016. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0167923616301373

[16] H. Kaur and J. Gera, "Effect of social media connectivity on success of crowdfunding campaigns," *Procedia computer science*, vol. 122, pp. 767–774, 2017.

[17] C.-Y. Lai, P.-C. Lo, and S.-Y. Hwang, "Incorporating Comment Text into Success Prediction of Crowdfunding Campaigns," p. 13, 2017.

[18] W. Wang, K. Zhu, H. Wang, and Y.-C. J. Wu, "The Impact of Sentiment Orientations on Successful Crowdfunding Campaigns through Text Analytics," *IET Software*, vol. 11, no. 5, pp. 229–238, Oct. 2017. [Online]. Available: https://digital-library.theiet.org/content/journals/10.1049/iet-sen.2016.0295

[19] K.-h. Lee, S.-h. Lee, and H.-c. Kim, "Predicting the success of crowdfunding campaigns using multimedia and linguistic features," *Journal of Korea Multimedia Society*, vol. 21, no. 2, pp. 281–288, Feb. 2018. [Online]. Available: https://doi.org/10.9717/KMMS.2018.21.2.281

[20] H. Zhao, B. Jin, Q. Liu, Y. Ge, E. Chen, X. Zhang, and T. Xu, "Voice of Charity: Prospecting the Donation Recurrence & Donor Retention in Crowdfunding," *IEEE Transactions on Knowledge and Data Engineering*, pp. 1–1, 2019. [Online]. Available: https://ieeexplore.ieee.org/document/8669972/

[21] F. Tan, X. Hou, J. Zhang, Z. Wei, and Z. Yan, "A Deep Learning Approach to Competing Risks Representation in Peer-to-Peer Lending," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 30, no. 5, pp. 1565–1574, May 2019. [Online]. Available: https://ieeexplore.ieee.org/document/8488590/

[22] L. Salahaldin, M. Angerer, S. Kraus, and D. Trabelsi, "A duration-based model of crowdfunding project choice," *Finance Research Letters*, vol. 29, pp. 404–410, Jun. 2019. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S154461231830271X

[23] J.-A. Koch and M. Siering, "The Recipe of Successful Crowdfunding Campaigns: An Analysis of Crowdfunding Success Factors and Their Interrelations," *SSRN Electronic Journal*, 2019. [Online]. Available: https://www.ssrn.com/abstract=3439202

[24] J. C. Kaminski and C. Hopp, "Predicting outcomes in crowdfunding campaigns with textual, visual, and linguistic signals," *Small Business Economics*, Jul. 2019. [Online]. Available: http://link.springer.com/10.1007/s11187-019-00218-w

[25] T. Wang, F. Jin, Y. Cheng *et al.*, "Early predictions for medical crowdfunding: A deep learning approach using diverse inputs," *arXiv preprint arXiv:1911.05702*, 2019.

[26] A. Kindler, M. Golosovsky, and S. Solomon, "Early prediction of the outcome of kickstarter campaigns: is the success due to virality?" *Palgrave Communications*, vol. 5, no. 1, p. 49, Dec 2019.

[27] L. Wu, Z. Li, H. Zhao, Z. Pan, Q. Liu, and E. Chen, "Estimating Early Fundraising Performance of Innovations via Graph-based Market Environment Model," *arXiv:1912.06767 [cs, stat]*, Dec. 2019, arXiv: 1912.06767. [Online]. Available: http://arxiv.org/abs/1912.06767

[28] W. Shafqat and Y.-C. Byun, "Topic Predictions and Optimized Recommendation Mechanism Based on Integrated Topic Modeling and Deep Neural Networks in Crowdfunding Platforms," *Applied Sciences*, vol. 9, no. 24, p. 5496, Dec. 2019. [Online]. Available: https://www.mdpi.com/2076-3417/9/24/5496

[29] J. Wang, H. Zhang, Q. Liu, Z. Pan, and H. Tao, "Crowdfunding Dynamics Tracking: A Reinforcement Learning Approach," *arXiv:1912.12016 [cs, stat]*, Dec. 2019, arXiv: 1912.12016. [Online]. Available: http://arxiv.org/abs/1912.12016

[30] A. Moritz and J. H. Block, "Crowdfunding: A literature review and research directions," in *Crowdfunding in Europe*, D. Brüntje and O. Gajda, Eds. Cham: Springer International Publishing, 2016, pp. 25–53. [Online]. Available: http://link.springer.com/10.1007/978-3-319-18017-5_3

[31] L. Collins and Y. Pierrakis, "The venture crowd," *Crowdfunding equity investment into business*, 2012.

[32] P. Centobelli, R. Cerchione, E. Esposito, and M. Raffa, "The revolution of crowdfunding in social knowledge economy: Literature review and identification of business models," *Advanced Science Letters*, vol. 22, no. 5, p. 1666–1669, May 2016.

[33] Mudambi and Schuff, "Research note: What makes a helpful online review? a study of customer reviews on amazon.com," *MIS Quarterly*, vol. 34, no. 1, p. 185, 2010.

[34] P. J. Danaher, G. W. Mullarkey, and S. Essegaier, "Factors affecting web site visit duration: A cross-domain analysis," *Journal of Marketing Research*, vol. 43, no. 2, p. 182–194, May 2006.

[35] Z. Jiang, "Virtual product experience: Effects of visual and functional control of products on perceived diagnosticity and flow in electronic shopping," *SSRN Electronic Journal*, 2004. [Online]. Available: http://www.ssrn.com/abstract=1400827

[36] J.-A. Koch and M. Siering, "Crowdfunding success factors: The characteristics of successfully funded projects on crowdfunding platforms," 05 2015.

[37] A. Bagheri, H. Chitsazan, and A. Ebrahimi, "Crowdfunding motivations: A focus on donors' layerspectives," *Technological Forecasting and Social Change*, vol. 146, pp. 218–232, Sep. 2019. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0040162518309223

[38] "Why would a project be suspended?"

[39] J. S. Hui, E. M. Gerber, and D. Gergle, "Understanding and leveraging social networks for crowdfunding: opportunities and challenges," in *Proceedings of the 2014 conference on Designing interactive systems - DIS '14*. Vancouver, BC, Canada: ACM Press, 2014, pp. 677–680. [Online]. Available: http://dl.acm.org/citation.cfm?doid=2598510.2598539

[40] C.-T. Lu, S. Xie, X. Kong, and P. S. Yu, "Inferring the impacts of social media on crowdfunding," in *Proceedings of the 7th ACM international conference on Web search and data mining - WSDM '14*. New York, New York, USA: ACM Press, 2014, pp. 573–582. [Online]. Available: http://dl.acm.org/citation.cfm?doid=2556195.2556251

[41] D. Zvilichovsky, Y. Inbar, and O. Barzilay, “Playing Both Sides of the Market: Success and Reciprocity on Crowdfunding Platforms,” *SSRN Electronic Journal*, 2013. [Online]. Available: http://www.ssrn.com/abstract=2304101

[42] T. Mitra and E. Gilbert, “The language that gets people to give: phrases that predict success on kickstarter,” in *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing - CSCW ’14*. Baltimore, Maryland, USA: ACM Press, 2014, pp. 49–61. [Online]. Available: http://dl.acm.org/citation.cfm?doid=2531602.2531656

[43] D. Frydrych, A. J. Bock, T. Kinder, and B. Koeck, “Exploring entrepreneurial legitimacy in reward-based crowdfunding,” *Venture Capital*, vol. 16, no. 3, pp. 247–269, Jul. 2014. [Online]. Available: http://www.tandfonline.com/doi/abs/10.1080/13691066.2014.916512

[44] D. J. Scheaf, B. C. Davis, J. W. Webb, J. E. Coombs, J. Borns, and G. Holloway, “Signals’ flexibility and interaction with visual cues: Insights from crowdfunding,” *Journal of Business Venturing*, vol. 33, no. 6, pp. 720–741, Nov. 2018. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0883902617300617

[45] A. Xu, X. Yang, H. Rao, W.-T. Fu, S.-W. Huang, and B. Bailey, “Show me the money! an analysis of project updates during crowdfunding campaigns,” *Conference on Human Factors in Computing Systems - Proceedings*, 04 2014.

[46] S. Chen, S. Thomas, and C. Kohli, “What Really Makes a Promotional Campaign Succeed on a Crowdfunding Platform?: Guilt, Utilitarian Products, Emotional Messaging, And Fewer But Meaningful Rewards Drive Donations,” *Journal of Advertising Research*, vol. 56, no. 1, pp. 81–94, Mar. 2016. [Online]. Available: http://www.journalofadvertisingresearch.com/lookup/doi/10.2501/JAR-2016-002

[47] V. Etter, M. Grossglauser, and P. Thiran, “Launch hard or go home!: predicting the success of kickstarter campaigns,” in *Proceedings of the first ACM conference on Online social networks - COSN ’13*. Boston, Massachusetts, USA: ACM Press, 2013, pp. 177–182. [Online]. Available: http://dl.acm.org/citation.cfm?doid=2512938.2512957

[48] M. D. Greenberg, B. Pardo, K. Hariharan, and E. Gerber, “Crowdfunding support tools: predicting success & failure,” in *CHI ’13 Extended Abstracts on Human Factors in Computing Systems on - CHI EA ’13*. Paris, France: ACM Press, 2013, p. 1815. [Online]. Available: http://dl.acm.org/citation.cfm?doid=2468356.2468682

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

[50] Y. Lin, P. Yin, and W.-C. Lee, “Modeling Dynamic Competition on Crowdfunding Markets,” in *Proceedings of the 2018 World Wide Web Conference on World Wide Web - WWW ’18*. Lyon, France: ACM Press, 2018, pp. 1815–1824. [Online]. Available: http://dl.acm.org/citation.cfm?doid=3178876.3186170

[51] V. Rakesh, W.-C. Lee, and C. K. Reddy, “Probabilistic Group Recommendation Model for Crowdfunding Domains,” in *Proceedings of the Ninth ACM International Conference on Web Search and Data Mining - WSDM ’16*. San Francisco, California, USA: ACM Press, 2016, pp. 257–266. [Online]. Available: http://dl.acm.org/citation.cfm?doid=2835776.2835793

[52] Q. Du, W. Fan, Z. Qiao, G. Wang, X. Zhang, and M. Zhou, “Money Talks: A Predictive Model on Crowdfunding Success Using Project Description,” p. 9, 2015.

[53] C. Cheng, F. Tan, X. Hou, and Z. Wei, “Success Prediction on Crowdfunding with Multimodal Deep Learning,” in *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence*. Macao, China: International Joint Conferences on Artificial Intelligence Organization, Aug. 2019, pp. 2158–2164. [Online]. Available: https://www.ijcai.org/proceedings/2019/299

[54] V. Butticè, M. G. Colombo, E. Fumagalli, and C. Orsenigo, “Green oriented crowdfunding campaigns: Their characteristics and diffusion in different institutional settings,” *Technological Forecasting and Social Change*, vol. 141, pp. 85–97, Apr. 2019. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S004016251731003X

[55] K. Sawhney, C. Tran, and R. Tuason, “Using language to predict kickstarter success,” 2016.

[56] S. Lee, K. Lee, and H.-c. Kim, “Content-based Success Prediction of Crowdfunding Campaigns: A Deep Learning Approach,” in *Companion of the 2018 ACM Conference on Computer Supported Cooperative Work and Social Computing - CSCW ’18*. Jersey City, NJ, USA: ACM Press, 2018, pp. 193–196. [Online]. Available: http://dl.acm.org/citation.cfm?doid=3272973.3274053

[57] K. Chen, B. Jones, I. Kim, and B. Schlamp, “Kickpredict: Predicting kickstarter success,” *Technical report, California Institute of Technology*, 2013.

[58] P.-F. Yu, F.-M. Huang, C. Yang, Y.-H. Liu, Z.-Y. Li, and C.-H. Tsai, “Prediction of Crowdfunding Project Success with Deep Learning,” in *2018 IEEE 15th International Conference on e-Business Engineering (ICEBE)*. Xi’an: IEEE, Oct. 2018, pp. 1–8. [Online]. Available: https://ieeexplore.ieee.org/document/8592623/

[59] T. Wang, F. Jin, Y. Hu, and Y. Cheng, “Early predictions for medical crowdfunding: A deep learning approach using diverse inputs,” *arXiv:1911.05702 [cs]*, Nov 2019, arXiv: 1911.05702. [Online]. Available: http://arxiv.org/abs/1911.05702

Arvind Srinivasan Department of Computer Science and Engineering, SRM Institute of Science and Technology, Kattankulathur, India.

Arvind Srinivasan was born in Hosur, India, in September 1998. He is currently pursuing the Bachelor of Technology degree in Computer Science and Engineering with SRM Institute of Science and Technology, Chennai, India, which he joined, in June 2016.

He worked as a Remote Software Development Intern at Tetrate, a Silicon Valley Startup housed in San Francisco, California, in June 2019. He worked as a summer intern in Cuedin Technologies, Chennai, India, in Jan 2018, and as an academic Intern at NUS, as part of the Global Academic Internship Programme organised in Jun 2018. His current research interests include Human-centred Computing, Deep Learning and Artificial Intelligence.

Akilandeswari P Biography text here.