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Perceived Value of Technology Product Features by Crowdfunding Backers: The Case of 3D Printing Technology on Kickstarter Platform

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by

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Abstract

Crowdfunding is an activity that gathers funds by drawing on a relatively small contribution from a relatively large number of individuals using the internet. One of the crowdfunding purposes is to fund entrepreneurial ventures. Modern crowdfunding activities—that utilize the internet—go back to 1997 and gained popularity in the music and video community. However, the most common platforms for entrepreneurial activities, including Kickstarter and IndieGoGo, have been established as recently as 2008. Thus the understanding of crowdfunding's dynamic is in its infancy.

Crowdfunding has been studied from various perspectives, primarily focusing on the factors that increase the platform's participation and determinants that make a campaign successful. Most literature considered general determinants for analyzing the outcome of a campaign. These approaches mediated the differences in project type by adjusting the impact of determinants from one project category to another. There are indications that mediation is not sufficient to explain the differences, especially in the technology category with a unique behavior—for instance, the technology category has the lowest rate of success yet the third-highest amount of raised money for successful projects on Kickstarter platform.

It is believed that the presence of videos and pictures on a project's campaign page has a positive influence on the campaign's success. However, a mandate of providing videos and pictures for technology products is not helpful to improve the success rate. On the other hand, a higher complexity compared to other types of products such as art, music,

film, or game explains the lower success rate. According to the diffusion of innovation theory, complexity impedes product adoption. The relative advantages of complex innovations are a vital attribute to overcome complexity impediment, especially when the decision for adoption is taken under a high amount of uncertainty.

In this dissertation, I studied the perceived value of technology-product features by crowdfunding backers to provide insights into what appeals to technology backers to support a complex and risky project. This approach combines *aspect and opinion extraction*—Double Propagation—to efficiently extract a comprehensive set of product features and *regularized logistic regression* to deal with the sparsity of product features and analyze the impact of technology features on the campaigns' success. Furthermore, I overcame the trade-off issue between statistical validation and detecting the impact of non-dominant features by utilizing a bootstrapping technique and marking identified advantages as "statistically verified" or "verified by subject matter expert."

This work mainly makes contributions to crowdfunding theory, including establishing product features as a success determinant, providing insights into the perceived value of the product, and overall providing a better understanding of the crowdfunding dynamic for technology products. This work also has a practical contribution by providing insights to project founders to utilize their crowdfunding campaign as a market research tool and better understand the demand for their product. Finally, on the methodological contribution, previously utilized techniques of *aspect and opinion extraction* in customer reviews context is expanded and adapted for crowdfunding context.

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1. Introduction

Acquiring capital for purposes such as charitable efforts and early-stage fundraising for start-ups is the main potential across all crowdfunding platform types. However, other potentials, including pre-sales, marketing, market research, and co-creation, depend on the platform type [1]. Thus, crowdfunding platforms provide a valuable opportunity for entrepreneurial activities, such as turning lead users into user entrepreneurs [2]. The main benefit is providing an alternative to traditional financing options—bank loans and creditors. A hedonism[1] crowdfunding platform among all three types—altruism, hedonism, and for-profit [3]—provides an opportunity to understand the market and demand for a product.

Understanding crowdfunding platforms' dynamic is vital for promoting entrepreneurship through the policy-making process—facilitating the use—and creating enough interests to increase participation. Dynamic of crowdfunding or interaction between *project initiators (founders)*, *fund providers (backers)*, and *intermediaries (crowdfunding platforms)* affects the success of crowdfunding enterprise which in return realizes platform potentials. Platform types, product types, characteristics and behavior of founders and backers, their motivations for participation, perceived risk in crowdfunding, the value propositions of crowdfunding, and success determinants of projects are among factors that influence the dynamics of a crowdfunding platform [1]. This study focuses on advancing the understanding of backers' motivations with regard to the platform and product type to support the entrepreneurial dynamism of crowdfunding platforms.

[1] Hedonism and altruism are used in this document as original source, although hedonistic and altruistic are the grammatically correct form.

This study intends to analyze what makes backers support technology products on hedonism crowdfunding platforms. Discussed motivations for backers are derived from crowdsourcing theories to this date. Some of these motivations are confirmed in the literature that focuses on success determinants of crowdfunding projects. However, there is a call for identifying more motivations and empirical validation of them in literature [1]. This study intends to address this known need and further specifies the motivations associated with supporting technology products on the hedonism crowdfunding platforms.

The closest theory that motivation for technology backers can be derived from is a diffusion of innovation theory [4]. This theory establishes that innovation is communicated through specific channels in a social system over time and adopted by members of the system. The diffusion rate of innovation depends on product's perceived attributes—relative advantage, complexity, compatibility, observability, and trialability. The crowdfunding campaign's success is used as a proxy for product adoption, which indicates whether there is enough motivation to adopt the product. The effect of communication channels and interaction among social systems on campaign success is covered in the literature. However, there is no research to address the impact of innovation itself on a campaign's success.

The complexity of technology products and higher risk due to relatively higher pledged money lowers the chance of altruism or recognition [5] as crowdfunding backers' primary motivations. Therefore, the product itself becomes the reward and the core motivation for supporting technology products. However, no prior research has examined the effect of innovation on backers' motivation to pledge money and, consequently, the campaign's success. This study's central questions are on the impact of technological aspects of a product on the campaign's success and its perceived value.

This research is designed to test the diffusion of innovation theory in the crowdfunding context. It examines whether there is a relationship between product features and the success of the campaign. Also, the factors that impact the perceived value of products are explored—mostly focusing on relative advantage of the product. Although there is no control on the innovativeness of the products launched on a platform, a better understanding of the perceived value by backers provides additional incentives to project initiators to choose "crowdfunding" over traditional alternatives and increase participation. The perceived value of a product is essential to turn marketing and market research potentials into real value for founders.

This research uses the same approach as the one applied to customer reviews. Previous research tried to establish the relationship between the opinion expressed toward product features of most interest to customers—perceived value of a product—and product demand. In customer reviews literature, there are three main steps. The first step is automating the aspect and opinion extraction from reviews. The second step, group the extracted features into categories to resolve aspects' language variation, and quantify categories. The third step, build a choice—demand-feature—model and analyze product features' effect on product demand. The same processes and steps are adopted for crowdfunding concepts. However, each process is modified based on the inherent differences between the context of customer reviews and crowdfunding.

Chapter 2, Review of Crowdfunding Dynamic and Success Factors, discusses the crowdfunding platform types and basics of the Kickstarter—crowdfunding platform which is the subject of this study. This chapter also includes reviews of backers' motivation and success factors of the crowdfunding campaigns. In the end, the backers' behavior and motivations are compared to technology product customers, and the research gaps are identified with regards to expected behavior. Chapter 3, Research Methodologies: Product Features Extraction and Classification, focuses on the methodologies used in this study to address the research questions. This chapter reviews techniques used for product aspect and opinion extraction and elaborates on the double propagation technique and logistic regression as the main techniques. Chapter 4, Research Design, lays out a step-by-step plan to adjust and implement methodologies discussed in Chapter 2 to fulfill this study's purpose. Chapter 5, Analysis and Results, describes the analysis's results in 3D printer projects. Chapter 6 discusses the results and answers research questions. Chapter 7, Chapter 8, and Chapter 9 explain the limitations, potential future research, and the research contributions, respectively.

2. Review of Crowdfunding Dynamic and Success Factors

The *"crowdfunding dynamic"* involves the interaction between *"founders," "backers,"* and *"platforms,"* impacting a crowdfunding campaign's success. The focus of this study is on backers' behavior and its effect on the platform dynamic. This chapter begins with reviewing crowdfunding platform types and describes the *Kickstarter* platform chosen for this study. It also examines the literature related to backers' behavior—backers' motivation and success determinants of a crowdfunding campaign. Section 2.4 provides the expected behavior of technology product backers through comparison to customers' response to an innovative product in the general market. In the end, the gaps are summarized, and the research objective and questions concerning each gap are explained.

2.1. Crowdfunding platforms

Crowdfunding platforms are categorized from various perspectives. From the type of return perspective, crowdfunding platform types are *"donation-based," "reward-based," "pre-selling," "lending,"* and *"equity-based"* [6]. However, considering multiple aspects of crowdfunding platforms such as project type, return type, risk, and platform functionalities, crowdfunding platforms are categorized as *"altruism," "hedonism,"* and *"for-profit"* [3]. The altruism platform is a donation-based type that focuses on sustainability and charity projects. The hedonism platform is the place for innovative and creative projects and products where backers support the project in exchange for pre-selling products or rewards. Backers invest in start-ups and either receive interest for lent money or share profit for acquired equity in a for-profit platform. This study focuses on hedonism platforms and the case of innovative products.

Kickstarter is the most popular hedonism platform and the subject of analysis for this study. Kickstarter is an independent public benefit company (PBC) based in Greenpoint, Brooklyn. It provides a crowdfunding platform for creative projects in 15 categories—art, comics, crafts, dance, design, fashion, film and video, food, games, journalism, music, photography, publishing, technology, and theater. Project, funding goal, creators, backers, and rewards are the fundamentals of Kickstarter. Kickstarter provides a web 2.0 platform to connect a creator—the person or team behind the project (a finite work with a clear plan to create something)—with potential backers who pledge money to help the project to succeed. The transaction mechanism between the creator and backers is controlled through a reward system. Rewards provide a clear explanation of what type of perks backers would receive in return for the amount of money they are pledging.

Reward-based crowdfunding platforms are following two models—*Keep-It-All (KIA)* or *All-Or-Nothing (AON)* model. KIA model lets founders keep the entire amount raised regardless of the campaign goal. On the other hand, the AON model funds campaign only if they meet the goal that has been set at the beginning of the campaign [7]. The funding goal is the estimated amount of money by the creator required to complete the projects and fulfill the promises made to backers in the reward section. The governing body of Kickstarter believes their AON strategy would make creators put more effort into the planning phase and have a better grasp of the budget scope. Consequently, the AON strategy reduces the risk of failure of bringing the projects to life. It is also believed that the AON strategy motivates and activates the community to rally behind the project that matters to them to guarantee enough support for the project's viability.

2.2. Backers' Motivations

Backers' engagement has an essential role in the success of crowdfunding. Previous research is stated various motivations for backers to invest and support a project. Social networks [8], [9], interaction with others [10], "herding" [10] and "free-riding" behavior [11], direct and regional identification [12], "return" motive [5], "recognition" motive [5], "social" reputation [13], "altruism" [5], "supportiveness"[14], interest in financial result or economic value [14], [15], identifying themselves with company or product [15], "innovation-oriented" [15], and "lead-user" characteristics [14] are among listed motivations. However, these motivations are general and not specified based on the crowdfunding categories—discussed in section 2.1.

Understanding the factors that motivate backers to invest is in its infancy and requires further research. This study intends to determine influential factors for the success of innovative technology products on hedonism platforms. A campaign's success is considered a proxy for strength of motivation among backers' for engaging in supporting a project. The literature on the success determinants of crowdfunding campaigns is reviewed in section 2.3. Most of the reviewed literature is carried their research on the Kickstarter platform. So, extracted determinants are directly related to hedonism platforms. Then, determinants are compared against the main elements of diffusion of innovation theory to establish a baseline for backers' motivation for supporting innovative technology products.

2.3. Success determinants of crowdfunding campaigns

Mollick [16] was among the first researchers to focus on the dynamic of the Kickstarter platform in 2014. As summarized in Appendix A, Mollick [16] examined the relationships between a various set of success factors and the success of the campaign. Considered success factors include campaign goal, duration of the campaign, the existence of campaign video, number of Facebook friends, number of backers, etc. Since then, several researchers have tried to establish the relationship between various factors and the Kickstarter campaign's success. Appendix A provides a taxonomy of literature studied the success determinant of crowdfunding platforms—overwhelmingly Kickstarter—and methodologies that have been used to analyze the effect of determinants. All the determinants extracted from the literature are summarized and categorized based on internal or external influences. The internal influences are categorized into three categories—"campaign," "creator(s)," and "backers'" features—based on the Kickstarter fundamentals. Social media and online promotion like blogs and press are considered as external influences.

and also related features extracted from the reviewed literature. These features are classified as features related to the crowdfunding campaign itself, founders of the campaign, funders or supporters of the campaign, and external determinants, mostly obtained from multiple social media platforms.

Table 1. shows internal influences distinguished as "campaign effect," "founders effect," "funders effect," and external influence consolidated in "external effect." Campaign effect are further categorized into basic, monetary, temporary or dynamic, media

richness, campaign's liveliness, quality of the campaign, and connectedness to other platforms. Founders effect is related to the founders experience and level of influence. Funders effect captures characteristics of funders and includes statistics on funders. External effect shows the influence of social media. Determinants extracted from literature—refer to Appendix A—are matched with the categories in Table 1.

Basic: general information about the campaign such as the year it was launched, the assigned category, etc.

Monetary: information related to financial aspects of the campaign, including the monetary goal of the campaign, pledged money at the end of the campaign, monetary information of reward section, etc.

Temporary or dynamic: this category provides insight on the progress of the campaign over a different period, such as accumulated pledged money in different time sections of the campaign, the accumulated number of backers, etc.

Media richness: this category captures the effect of media such as the videos, images, etc., in conveying the campaign's message and attracting funders.

Quality of campaign: this involves the textual content of the campaign, including project description, reward description, updates, etc. Various approaches have been taken to quantify or classify these contents as a measure of a campaign's quality, such as the number of words, number of sentences, sentence structure, and so forth.

Connectedness to other platforms: this represents how much a given campaign leverages other platforms to keep its audience engaged through the process or use those platforms to draw attention toward the campaign.

Founders' experience and influence level: it represents founders' experience level by considering the number of previously created projects, the time that the creator has been on the platform before starting their first project, and so forth. Also, it considers the creators' influence level based on established reciprocity relation with other founders or their connectedness on social media and so on.

Funders' characteristics and statistics: it considers the magnitude of support, the effect of funders' interest in particular subject and creators, and so on.

Social media effects: measures the effectiveness of social medias' role in raising awareness of the campaign.

Various combinations of success determinants—summarized in Table 1—and methodologies are used to analyze crowdfunding platforms' dynamics from different perspectives. Most of the recent analyses are focused on predicting the success or failure, number of backers, and the campaign's financing rate. Also, there are attempts to suggest potential backers for live projects based on previous campaign experiences. Other types of analysis include distinguishing progressive from ordinary projects based on their features or do some post-campaign research, such as predicting delivery delay.

	Category	Success Determinant
Campaign Effect	Basic	launch date, duration, main category, sub category, featured, year, is launched in USA, is launched in Europe,
	Monetary	goal, no. of reward levels, minimum pledge, date and time of pledge, amount pledged, is donation, is pre-selling, had limit on reward level, percent funded, currency, growth rate, maximum pledge, average pledge, STD of pledge, type of financing,
	Temporary / dynamic	accumulated pledged money, accumulated no. of backers, first day pledged money, no. of first day backers no. of first day comments, no. of first day Facebook shares, accumulated pledged money over first three days, accumulated no. of backers over first three days, no. of promotional tweets over first three days,
	Media richness	video presence, image presence, video duration, no. of images in project description, no. of images in project updates, no. of videos in project description, no. of videos in project updates, YouTube video presence, no. of YouTube video view
	Liveliness of campaign	no. of updates, no. of comments, no. of FAQs, had quick updates,
	Quality of campaign	project description (text, general phrases, psycholinguistic category, sentiment, sentiment score, no. of sentences, no. of words, no. of characters, SMOG grade, FOG index, Flesch ease score, Flesch-Kincaid grade level, had spelling error, sentence structure), reward description(general phrases, SMOG grade, no. of sentences), update title (no. of words), update text (update theme —ratio of update theme to no. of updates, ratio of no. of updates in campaign phase(initial, middle, final) to total no. of updates in each theme, no. of words, Flesch ease score), project title (no. of words), risk and challenge description (text, no. of words, psycholinguistic category), FAQs (no. of words), Project Video (product-related factors — relevance, complexity, involvement, purchase intent —, video-related factors — perception of video duration, video and audio quality, attitude toward video.),
	Connectedness to	Facebook connected blog entries no. of URLs in no. of URLs in updates

	Category	Success Determinant		
	other platforms	twitter connected YouTube connected	project description	dedicated website
Founders Effect	Founders experience and influence level	no. of created projects, no. of backed projects, categories of backed projects, conditional probability of user interest in category, distribution of backed projects under the main categories, conditional probability of user interest in creator, no. of comments user made in past, creator's Facebook profile features	no. of Facebook friends no. of website linked in a user profile, SMOG grade of bio description, no. of sentences in bio description, interval between joining date and project lunch date, success rate of backed projects, success rate of created projects, had created project(s),	created project and succeeded, created project and never succeeded, had backed project(s), target project owner backed source projects, source project succeeded, is target project in the same category as source project, is the target project size the same as source project,
Funders Effect	Funders characteristics and statistics	no. of backers no. of projects with co-backers	no. and rate of success of co-backed projects no. and rate of first time backers	the influence rate of community over backers
External Effect	Social media effects	no. of tweets no. of replies no. of retweets no. of users who tweeted no. of followers no. of followings no. of favorites	no. of lists no. of tweets during campaign no. of tweets with "Kickstarter" SMOG grade of aggregated tweets during campaign	no. of promotional tweets no. of promoters the tie strength the bi-connected components page rank of promoters no. of Facebook shares

Table 1 - Features that may affect the outcome of the crowdfunding campaign

2.4. The effect of product features on backers' engagement

Success determinants are related to the campaign, founders, funders, and external effects, as shown in Table 1. The strength of determinants is not homogenous across all product categories. For instance, video and image on a campaign page are considered a positive influence on the campaign's success [16]. However, the technology category has the lowest success rate on Kickstarter despite having videos and images in all its campaign—mandated by Kickstarter policy. So, more factors influence the success of technology products that haven't been considered before. If founders seek funds for their innovative endeavors, it is reasonable to assume that innovation itself motivates backers to support a project. However, being innovation-oriented is the only backers' motivation related to the product, not the campaign aside from success determinants. This section intended to discuss product features' effect on customer choice in the general market, differences between general market and crowdfunding platform, and expected effect of product features for technology products on a crowdfunding platform.

2.4.1. The effect of product features on customer choice in the general market

"Diffusion of adoption" theory is the process that discusses how innovation gets adopted over time. Four main elements affect the rate of adoption—*"innovation itself," "communication channel," "time,"* and *"social system"* [4]. Innovation is assessed based on five attributes: *"relative advantage," "compatibility," "complexity," "triability,"* and *"observability"* [4]. Traditionally, customer preferences toward price and product attributes are measured using market data and experiment—"revealed preferences"—and direct and indirect surveys—"stated preferences" [17]. However, the newer approach considers customer reviews to predict product demands based on the discussed product features and associated opinions [18]. Web 2.0 application—digitalized two-way interaction utilizing the internet—provides a medium for consumers to state their opinion

toward product features in a free, large-scale, fast, and cost-effective way. The credibility and trustworthiness of reviews increase their influence over the social system over time.

2.4.2. Difference between general market and crowdfunding platform

The most significant differences between the general market and crowdfunding platforms are product triability, observability, and availability. Backers are taking more risk in crowdfunding platforms by making a decision under a higher amount of uncertainties. Involved risk and lack of options—caused by limited campaign period and investment opportunity—lower the demand for products on a crowdfunding platform. So, it is vital to understand the effect that these differences have on the perceived relative advantage of a product on a crowdfunding platform compared to the general market—measured by approaches discussed in 2.4.1.

2.4.3. The expected effect of product features on technology backers' engagement

Ordinary people are unlikely to support technology projects. On the other hand, technology-savvy people would back the technology project if they can appreciate and value the project and ensure that the campaign will be successful [19]. Technology products have higher complexity than other innovative products such as games, design, art, music, etc. Diffusion of innovation theory expects that complexity adversely affects the adoption rate of a product [4]. This barrier reflects in the statistic of Kickstarter[2]. The technology category has the lowest success rate, as of January 2021, with about a 21% success rate than the 38% average success rate on the Kickstarter platform.

[2] https://www.kickstarter.com/help/stats

Complex buying behavior is expected for complex products—mostly expensive, bought infrequently, and risky—where buyers first develop an attitude toward the product and then take action [20]. For innovative products, the product's perception is shaped by gathered information, considering alternatives, and assessing innovation [21] based on attributes discussed in section 2.4.1. Supporting technology products on hedonism platforms is similar to complex buying behavior. However, the assessment process is different based on the differences discussed in section 2.4.2. In a nutshell, backers use the same information—product features and price—to develop an attitude toward products. The importance of providing information about a product in a campaign video—especially in technology products—is previously confirmed [22]. It is expected that crowdfunding backers process this information differently compared to customers in the general market due to higher involved risk.

2.5. Research Gap

Crowdfunding is a novel approach to fund ventures and projects via a large number of small funds as an alternative to traditional financiers such as banks, capital ventures, and so on. However, this fast-growing area—crowdfunding—is understudied despite rapid advancement in practice and policy [16], [23]. As established in section 2.4, it is expected that innovation itself motivates crowdfunding technology backers to support a project. While product observability and triability are very limited on crowdfunding platforms, perception toward the product is shaped by providing information on product features and pledged amounts. However, there is no prior study of the effect of product features on campaign success. This study intends to analyze the relationship between technology product features and the success of campaign. This relationship can serve as a proxy to confirm that the product itself influences backers' motivation. This study focuses on how backers get motivated to adopt innovation by supporting projects on crowdfunding platforms based on diffusion of innovation theory by answering the following research questions. The summary of the research gaps, objectives, and questions is stated in Table 2.

Q1- Do principals of diffusion of innovation theory apply to the case of crowdfunding of technology products—with the focus on innovation element?

As discussed in section 2.4.1, the main elements of diffusion of innovation theory include innovation, communication channel, time, and social system [4]. The influential features on the campaign's success—gathered from literature—are related to communication channels and social systems. These features are categorized regarding time—during or beyond the campaign period—and relatedness to crowdfunding platforms or external platforms like Tweeter, as shown in Table 1. It is expected that product features influence the outcome of a crowdfunding campaign. However, this effect isn't investigated so far and is identified as a gap in this study. This research aims to analyze whether there is a relationship between product features and the success of a technology campaign.

Q2- What are the relative advantages of technology products in a crowdfunding environment?

Time affects the diffusion of innovation in three ways—innovation-decision process, innovativeness of product, and innovation's rate of adoption. The effect of time on the decision process is already covered in the literature [24], [25]. This study aims to analyze product features' effect regarding time or product innovativeness effect on campaign success. Among the five perceived attributes of a product, relative advantage has the most dependency on time. The reason for focusing on the relative advantage is that the trialability, observability, compatibility, and complexity are either not applicable in the crowdfunding environment or hard to measure. However, the complexity effect is discussed in product category and technology level rather than product level. This study intends to explore the effect of time and price on the relative advantage of technology products on a crowdfunding platform. The relative advantages are studied concerning the product novelty and novelty-price dynamic and its effect on the campaign's outcome. This study also tries to find other factors such as quality that affect the relative advantages of a product. In the end, the relative advantages of a product on crowdfunding platforms are compared to the advantages of a product in the general market regarding the discussed differences of crowdfunding environment and general market in section 2.4.2.

Gaps	Objectives	Research Questions
The perceived value of a product: The literature has not formulated the product's effect on persuading and motivating backers to support a project. The literature emphasizes the impact of running and managing crowdfunding campaigns—raising awareness about the campaign, founders' previous experiences and successes, etc.—on creating a successful venture.	Have a better understanding of technology backers' motivation and its effect on hedonism platform dynamics.	Do principals of diffusion of innovation theory apply to innovative technology products on crowdfunding platforms—with the focus on innovation element?
Turning potential into reality: Currently, there is no guidance in the literature for project initiators about using crowdfunding platforms for market research and accurate interpretations of the success and failure of a campaign concerning the demand for a product.	Provide guidance to entrepreneurs via a better understanding of the demand for their products.	What are the relative advantages of technology products in a crowdfunding environment?

Table 2 - Summary of gaps, research objectives, and research questions.

3. Research Methodologies: Product Features Extraction and Classification

Chapter 2 explains this study's objective to analyze product features' effect on the campaign's success. A combination of product features extraction and classification methods is required to address the identified gaps and fulfill research objectives. This chapter discusses chosen techniques for product features extraction—double propagation—and classification—penalized logistic regression. Chapter 4, Research Design, explains how these techniques are implemented.

Section 3.1 provides an overall view of the product feature extraction method. It discusses the general steps are required for extracting features from unstructured text. It also reviews existing approaches and elaborates on the double propagation technique that fits the needs of the crowdfunding context. Section 3.2 explains the logistic regression technique used to classify campaigns according to their success or failure. It also elaborates on the feature selection and validation process—regularization, cross-validation, and bootstrapping of logistic regression.

3.1. Automatic product feature extraction

The abundance, availability, and significance of the implication of online opinion on products generated by consumers or third parties has attracted so many research interests. Blogs, online news platforms, e-commerce, web 2.0, and social media all together are contributed to the existence of such information. The product features/aspect and sentiment mined from these online mediums are useful for marketing, pricing strategies, new product development, etc. Aspect and opinion extraction techniques are well-developed to extract expressed opinions toward product features, mostly for customer reviews. Numerous researches explored how to automate the extraction process. Almost all the processes follow three steps—*preprocessing*, *extraction* of candidate features/aspects of product and opinion toward them, and *pruning* [26]–[29]. However, the implementation of each stage varies across the approaches.

Preprocessing is a combination of tasks to clean and normalize the text and enrich textual data. Text cleaning tasks deal with word variant or misspelling and remove less valuable and noisy words. The purpose of text normalization tasks is to transform the text format into a single canonical form. Textual information can be enriched by adding information such as lexical categories and grammatical structure. The enriching process includes *tokenization*, *Part-of-Speech* (*POS)* tagging, *dependency relation*, and *syntactic* analysis, deletion of *stopwords*, *stemming*, *fuzzy matching*, and so on [27], [28]. The extraction phase usually is a combination of actions to create a tuple of non-subjective features or subjective features and associated opinions. These tuples are candidate features. Actual features are selected from a pool of candidates by pruning the noises.

3.1.1. Preprocessing

The preprocessing tasks are for preparing the text consisting of tokenization, POS, lemmatization, stemming, etc. Each task is elaborated further below.

Part of speech tagging [30]: also known as POS, word classes, or syntactic categories, "is the process of assigning a part-of-speech marker to each word in an input text. The input to tagging algorithm is a sequence of (tokenized) words and a tagset, and output is a sequence of tags, one per token" [30]. There are several algorithms to process POS, including Hidden Markov Model (HMM), the Maximum Entropy Markov Model (MEMM), the Recurrent Neural Network (RNN), and a rule-based approach.

Words such as a *book* can have different syntactic roles in various sentences. For example, the book is a verb in "*book that flight*" and a noun in "*hand me that book*." 14-15% of the vocabulary can take an ambiguous role in the sentence. However, 55-67% of the text can be filled with these ambiguous words because of their commonalities. POS algorithms take various approaches to address the ambiguity of the words. So far, the accuracy of these algorithms' performance to resolve the word ambiguity is around 97%.

Table 3 illustrates the word classes or part-of-speech tags based on Penn Treebank. Word classes have two subcategories—*close* class and *open* class. Closed classes are the ones that rarely get new members, while in open classes, new members are continually being created or borrowed. English has four open classes—*nouns*, *verbs*, *adjectives*, and *adverbs*. The following elaborates on each class.

Tag	Description	Example	Tag	Description	Example	Tag	Description	Example
CC	coordinating conjunction	*and, but, or*	PDT	predeterminer	*all, both*	VBP	verb non-3sg present	*eat*
CD	cardinal number	*one, two*	POS	possessive ending	*'s*	VBZ	verb 3sg pres	*eats*
DT	determiner	*a, the*	PRP	personal pronoun	*I, you, he*	WDT	wh-determ.	*which, that*
EX	existential 'there'	*there*	PRP$	possess. pronoun	*your, one's*	WP	wh-pronoun	*what, who*
FW	foreign word	*mea culpa*	RB	adverb	*quickly*	WP$	wh-possess.	*whose*
IN	preposition/ subordin-conj	*of, in, by*	RBR	comparative adverb	*faster*	WRB	wh-adverb	*how, where*
JJ	adjective	*yellow*	RBS	superlatv. adverb	*fastest*	$	dollar sign	$
JJR	comparative adj	*bigger*	RP	particle	*up, off*	#	pound sign	#
JJS	superlative adj	*wildest*	SYM	symbol	+,%, &	“	left quote	‘ or “
LS	list item marker	*1, 2, One*	TO	“to”	*to*	”	right quote	’ or ”
MD	modal	*can, should*	UH	interjection	*ah, oops*	(	left paren	[, (, {, <
NN	sing or mass noun	*llama*	VB	verb base form	*eat*	)	right paren	],), }, >
NNS	noun, plural	*llamas*	VBD	verb past tense	*ate*	,	comma	,
NNP	proper noun, sing.	*IBM*	VBG	verb gerund	*eating*	.	sent-end punc	. ! ?
NNPS	proper noun, plu.	*Carolinas*	VBN	verb past part.	*eaten*	:	sent-mid punc	: ; ... – -

Table 3 - Penn Treebank part-of-speech tags [30].

Nouns: are falling into two classes—proper and common nouns. Proper names are the name of specific persons or entities and usually capitalized. Common nouns are divided into count and mass nouns. Count nouns can be counted and be singular or plural. By contrast, mass nouns are conceptualized as a homogonous group and not countable.

- Verbs: refers to action or processes, and in English, they have inflections, third person, progressive, and past participle.
- Adjectives: refers to properties or qualities of entities. English has adjectives for color, age, value, and so on.
- Adverbs: word classes have semantic tendencies. In the adverb case, semantic coherence can be viewed as a modifier of verbs, another adverb, or a verb phrase. Adverbs can be classified into directional/locational adverbs—*home*, *here*, *downhill*—, degree adverbs—*extremely*, *very*, *somewhat*—, manner adverbs—*slowly*,

slinkily, *delicately*—, and temporal adverbs—*yesterday*, *Monday*—. Adverbs can be tagged as nouns because of their heterogeneous nature.

Closed classes include prepositions, particles, determiners, conjunctions, pronouns, auxiliary verbs, and numerals in English. The followings elaborate on these classes.

- Prepositions: occurs before nouns and includes *on*, *under*, *over*, *by*, and so forth. Semantically indicate spatial or temporal relations and marking the agent.
- Particles: is used in combination with verbs and resembles a preposition or adverb though it does not carry its meaning. A combination of particles and verbs that act as a single semantic unit is called a verb phrase.
- Determiners: is a subtype of the article and include *a*, *an*, *the*, *this*, and *that*. Determiner often marks the beginning of the noun phrase, *a* and *an* mark noun phrase as indefinite while the mark noun phrase as definite.
- Conjunctions: either coordinating or subordinating conjunction joins phrases, clauses, or sentences. Coordinating conjunction such as *an* join two equal statements while subordinating like *that* join the clause with the main verb, also called complementizers.
- Pronouns: including personal pronouns—*you*, *I*, *she*, and so on—, possessive pronouns—*my*, *your*, *her*, and so forth—, wh-pronouns—*what*, *whom*, *who*— are the shorthand that refers to noun phrase, entity, person, or entity.
- Auxiliary verbs are the subtype of the main verb and mark the main verb's semantic feature. Auxiliary verbs include the copula verb *be* and a modal verb such as *have*.

Copula connects the subject with certain kinds of predicate nominals and adjectives, and modals mark the mood associated with the event depicted by the main verb.

Other closed classes in English include numerals (*one*, *two*, *three*, ...), interjections (*oh*, *hey*, ...), negatives (*no*, *not*), politeness markers (*please*, *thank you*), greetings (*hello*, *goodbye*), and the existential *there*.

POS tagging determines the lexical class of each word. In comparison, tokenization, lemmatization, stemming, and sentence segmentation are a set of tasks to convert text to a more convenient and standard format. The followings explain each task further:

Tokenization [30]: separating or tokenizing the words based on white spaces, defined words in WordNet, and so forth.

Lemmatization [30]: is the task of determining the common root of words with a different surface. For instance, sing is the common lemma for *sang*, *sung*, and *sings*, and a lemmatizer maps all of the various forms to sing.

Stemming [30]: is a simpler version of lemmatization and mainly strip suffix from the end of the words.

Dependency parsing [30]: parsing the sentence's syntactic structure regarding the words and an associated set of directed binary grammatical relations amongst the words. The dependency structure consists of a binary link between head and dependent. Binary relations help to specify the head-dependent pair and the role that the dependent plays concerning the head.

3.1.2. Candidate feature and opinion extraction

The step after preprocessing of text is the extraction of feature and opinion candidates. Though, the opinions are not used in the analysis, this study used opinion to have comprehensive pool of candidates to identify the main characteristics of product that highlighted in the description. This section provides an overview of extraction techniques and elaborates on the double propagation approach chosen for this study.

3.1.2.1. Extraction techniques overview

The extraction phase usually is a combination of actions to create a tuple of non-subjective features or subjective features and associated opinion and classification of the tuples. They are categorized into *statistical-based* and *rule-based* methods [28]. Based on the need for a training dataset, the methods in each category can be further classified into supervised or unsupervised. In another way, they can be categorized into four main categories—*lexical terms frequency*, *syntactic relations*, *supervised learning*, and *topic models* [31].

Hu & Liu's approach [27] for opinion feature mining from customer reviews is one of the pioneering efforts in lexical term frequency approach. Their approach considers three words or less noun phrases as a product feature candidates. Multiple pruning steps are applied including selecting most frequent candidates. Opinion associated with these frequent items are utilized to select important less frequent features.

Rule-based category uses syntactic relations and fall under unsupervised and weak semi-supervised ruled-based categories. Despite the dominance of the statistical approach, the rule-based model does not rely on either large-scale annotated or training corpora compared to the statistical model [28]. *Double propagation (DP)* is considered the state-of-the-art rule-based method. There are other efforts Such as *RubE* [28] that tries to have more comprehensive approach to extract product features. It considers indirect dependency to identify non-subjective features and certain lexico-syntactic part-whole patterns to discover parts of device in addition to subjective features that covered by DP's direct dependency rules.

Sequence models are the (semi-)supervised learning utilized to extract product aspects. *Hidden Markov Model (HMM)* is a sequence model widely considered for aspect extraction, although there is a concern about its performance in real-life problems [32]. *Conditional Random Fields (CRF)* is an undirected sequence model that overcomes HMM issue by relaxing the strong assumption made by HMM [32].

Several topic modeling approaches include the well-known *Latent Dirichlet Association (LDA)* and its several variations [33]. The topic modeling approaches aim to uncover topics in documents corresponding to the product [33]. Though relating topics to product aspects is the challenge of the topic modeling approach, it automatically combines the entity resolution step with extraction.

Double propagation (DP)—a rule-based approach—is chosen for this study. The main reason is the easier training and implementation process of DP than supervised learning and topic models. Besides, the DP outperforms the statistical approach—term frequency—in finding and extracting product features and associated opinions, particularly in applications with a small corpus [29]. It also combines the pruning with the extraction process and results in candidates with less noise [29]. The suitability of DP rules detecting product features discussed in Appendix C. The ability of double propagation to eliminate noise is discussed in Appendix D.

3.1.2.2. Double propagation approach

Qiu et al. [29] utilize double propagation to carry opinion word and feature extraction. Propagation rules are defined based on the three types of relations—between opinion word and feature (*OF-Rel*), between Features themselves (*FF-Rel*), and between opinion word (*OO-Rel*). In this rule-based approach, dependency grammar is employed to describe *OF-Rel*, *FF-Rel*, and *OO-Rel* syntactically. In the dependency grammar, two words are directly and indirectly depending on each other via syntactic relation.

POS tagging and dependency parsing are preprocessing steps that have been done using the Stanford POS Tagging Tool and MiniPar in [29]. Qiu et al. [29] considered adjectives as opinion words and nouns as features. So, *JJ* (adjectives), *JJR* (comparative adjectives), and *JJS* (Superlative adjectives) are the tags associated with opinion words. At the same time, *NN* (singular nouns) and *NNS* (plural nouns) are the tags associated with features. Also, considered dependency relations that can describe the *OF-Rel* include *mod*, *pnmod*, *subj*, *s*, *obj*, and *obj2*. In contrast, conj is regarded as potential dependency relation for *OO-Rel* and *OF-Rel*. Table 4 provides a description and an example of each dependency relation.

Dependency Relation	Description	Examples
mod	The relation between a word and its adjacent modifier	The computer has a good screen. *(good $\rightarrow$ mod $\rightarrow$ screen)*
pnmod	Post nominal modifier	Determiners, adjectives, relative clauses, and quantifiers.
subj	Subject of verb	"iPod" is the best mp3 player. *(best $\rightarrow$ mod $\rightarrow$ player $\leftarrow$ subj $\leftarrow$ iPod)*
s	Surface subject	The LCD should be used. *(LCD $\rightarrow$ s $\rightarrow$ used)*
obj	Object of verb	Canon "G3" has a great lens. *(lens $\rightarrow$ obj $\rightarrow$ has $\leftarrow$ subj $\leftarrow$ G3)*
obj2	Second object of ditransitive verb	I will give you a very good computer. *(computer $\rightarrow$ obj2 $\rightarrow$ give)*
conj	Conjuction	The camera is amazing and "easy" to use. *(easy $\rightarrow$ conj $\rightarrow$ amazing)*

Table 4- *OF-Rel* dependency relations [34]

Four elements are needed to formulate the relationship between opinion and feature—*OF-Rel*, *OO-Rel*, and *FF-Rel*—including head word, dependent word, dependency relation, and dependency direction. These relationships are presented by quadruple. For instance, *<JJ, DD, mod, NN>* is one of the formulas representing *OF-Rel*. The relation formula is generalized as much as possible to define the relation rule, which has been fed to the propagation process for opinion and feature extraction, as shown in Table 5.

The observation column illustrates the generalized dependency pattern between the head and the dependent word. For instance, *O* → *O-Dep* → *F* means opinion words directly depend on feature through syntactic dependency relation *O-Dep*. All the rules in Table 5. follow a direct dependency pattern since indirect dependency exists in the formal text and text like customer reviews considered informal.

RuleID	Observations	Constraints	Output	Examples
$R1_1$	$O \rightarrow O\text{-}Dep \rightarrow F$	$O \in \{O\}$ $O\text{-}Dep \in \{MR\}$ $POS(F) \in \{NN\}$	*Feature = F*	The phone has a good "screen". *(good → mod → screen)*
$R1_2$	$O \rightarrow O\text{-}Dep \rightarrow H \leftarrow F\text{-}Dep \leftarrow F$	$O \in \{O\}$ $O/F\text{-}Dep \in \{MR\}$ $POS(F) \in \{NN\}$	*Feature = F*	"iPod" is the best mp3 player. *(best → mod → player ← subj ← iPod)*
$R2_1$	$O \rightarrow O\text{-}Dep \rightarrow F$	$F \in \{F\}$ $O\text{-}Dep \in \{MR\}$ $POS(O) \in \{JJ\}$	*Opinion = O*	
$R2_2$	$O \rightarrow O\text{-}Dep \rightarrow H \leftarrow F\text{-}Dep \leftarrow F$	$F \in \{F\}$ $O\text{-}Dep \in \{MR\}$ $POS(O) \in \{JJ\}$	*Opinion = O*	
$R3_1$	$F_{i(j)} \rightarrow F_{i(j)}\text{-}Dep \rightarrow F_{i(j)}$	$F_{i(j)} \in \{F\}$ $F_{i(j)}\text{-}Dep \in \{CONJ\}$ $POS(F_{i(j)}) \in \{NN\}$	*Feature* $= F_{i(j)}$	Does the player play DVD with audio and "video"? *(video → conj → audio)*
$R3_2$	$F_i \rightarrow F_i\text{-}Dep \rightarrow H \leftarrow F_j\text{-}Dep \leftarrow F_j$	$F_i \in \{F\}$ $F_i\text{-}Dep == F_j\text{-}Dep$ $POS(F_j) \in \{NN\}$	*Feature* $= F_j$	Canon "G3" has a great lens. *(lens → obj → has ← subj ← G3)*
$R4_1$	$O_{i(j)} \rightarrow O_{i(j)}\text{-}Dep \rightarrow O_{i(j)}$	$O_{i(j)} \in \{O\}$ $O_{i(j)}\text{-}Dep \in \{CONJ\}$ $POS(O_{i(j)}) \in \{JJ\}$	*Opinion* $= O_{i(j)}$	The camera is amazing and "easy" to use. *(easy → conj → amazing)*
$R4_2$	$O_i \rightarrow O_i\text{-}Dep \rightarrow H \leftarrow O_j\text{-}Dep \leftarrow O_j$	$O_i \in \{O\}$ $O_i\text{-}Dep == O_j\text{-}Dep$ $POS(O_j) \in \{JJ\}$	*Opinion* $= O_j$	If you want to buy a sexy, "cool", accessory-available mp3 player, you can choose iPod. *(sexy → mod → player ← mod ← cool)*

Table 5- Rules to extract direct dependency

The constraints column shows the potential sets for elements in the observed dependency pattern. *{NN}* is a set of POS tags for possible features which contain *NN* and *NNS*. *{JJ}* is a set of POS tags for potential features which contain *JJ*, *JJR*, and *JJS*. *{MR}* is a set of dependency relation between opinion and feature which contains *mod*, *pnmod*, *subj*, *s*, *obj*, and *obj2*. *{Conj}* is a set of dependency relation amongst opinion and feature which contains conj only.

In the constraint section, "==" means the same or equivalent, and *{O}* and *{F}* refers to the seed or extracted opinions and extracted features, respectively. The output of rules is either opinion words or features, which is the purpose of the rule to identify. Double propagation uses these rules to extract opinion words and features. The following shows the propagation steps and rules associated with each step.

i. Extracting targets using opinion words ($R1_1$ & $R1_2$)
ii. Extracting targets words using extracted targets ($R3_1$ & $R3_2$)
iii. Extracting opinion words using the extracted targets ($R2_1$ & $R2_1$)
iv. Extracting opinion words using both the given and extracted opinion words ($R4_1$ & $R4_2$)

The overview of the detailed implementation of the propagation algorithm is shown below, along with the input and output of the algorithm. Since double propagation is the weakly semi-supervised approach, it requires a small set of opinion seeds—a set of adjectives—to start the propagation process. The opinion seed used in this study is shown in the input line of the following DP pseudo code.

***Input**: Opinion Word Dictionary {O} = {'high', 'low', 'available', 'best', 'affordable'}*

***Output**: Extracted Features {F}, Expanded Opinion Lexicon {O-Expanded}*

Function:

1.{O-Expanded} = {O}
2.$\{F_i\} = \emptyset, \{O_i\} = \emptyset$
3. for each parsed sentence in R
4. if(Extracted features not in {F})
5. Extracted features $\{F_i\}$ using $R1_1$ and $R1_2$ based on opinion words in {O-Expanded}
6. endif
7. if(Extracted opinion words not in {O-Expanded})
8. Extracted new opinion words $\{O_i\}$ using $R4_1$ and $R4_2$ based on opinion words in {O-Expanded}
9. endif
10. endfor
11. Set $\{F\} = \{F\} + \{F_i\}$, {O-Expanded} = {O-Expanded} + $\{O_i\}$
12. for each parsed sentence in R
13. if(Extracted features not in {F})
14. Extracted features {F} using $R3_1$ and $R3_2$ based on opinion words in $\{F_i\}$
15. endif
16. if(Extracted opinion words not in {O-Expanded})
17. Extracted new opinion words {O'} using $R2_1$ and $R2_2$ based on features in $\{F_i\}$
18. endif
19. endfor
20. Set $\{F_i\} = \{F_i\} + \{F'\}, \{O_i\} = \{O_i\} + \{O'\}$
21. Set {F} = {F} + {F'}, {O-Expanded} = {O-Expanded} + {O'}
22. Repeat 2 until size $(\{F_i\}) = 0$, size $(\{O_i\}) = 0$

3.1.3. Pruning

Pruning is the step to filter the noise in the pool of aspect and opinion candidates. Several pruning approaches include compactness pruning [27], redundancy pruning, pruning based on clauses [29], etc. Most extraction approaches one step pruning after extraction step, while double propagation uses two-step pruning. The first pruning step tries to reduce noise in the extraction step by limiting dependency relations to define only the relation of aspects and opinion. The second step is like other approach applying pruning techniques after extraction step if it required. Thoroughly pruned candidates are essential for automating the aspect grouping. However, this study does not automate categorizing the product features, making the additional pruning step unnecessary.

3.2. Classification

Logistic regression is a probabilistic discriminative classifier suitable for discovering the link between features or cues and a given outcome. Logistic regression is classified into two classes—*binary* and *multinomial* logistic regression. Binary logistic regression classifies the observations into two classes, while multinominal logistic regression does the same for more than two classes. The focus of this section is on binary logistic regression.

Logistic regression is a supervised approach that establishes link input and output in two steps. The discriminative model focuses only on valuable input features that nearly separate the classes, also called the classes' evidence. So, in the first step, the probability is generated by calculating the weighted sum of the class's evidence and passing the result through a sigmoid function [30]. In the second step, the decision is made about classification based on the threshold [30]. Binary logistic regression uses a *sigmoid* classifier to make such a decision. Equation (1) to Equation (5) shows the single input, single output model's decision-making process. Where x is a single input observation represented by a vector of features $[x_1, x_2, ..., x_n]$, and y is output with two classes. The output (y) can be 1 or 0, which shows if the observation is a member of the class or not.

The sigmoid classifier's first goal is to calculate $P(y=1|x)$—the probability of an observation being a member of the class. This task can be done by calculating z—the weighted sum of input observation— and passing it to a sigmoid function. Z is calculated by sum the multiplication of the vector of weight (w_i) and input vector (x_i) and adding the bias term (b) to the result of the weighted sum. Logistic regression learns the vector of weight (w_i) and bias term (b) or intercepts from the training data set.

$$z = \left(\sum_{i=1}^{n} w_i x_i\right) + b = w.x + b \tag{1}$$

$$y = \sigma(z) = \frac{1}{1+e^{-z}} \tag{2}$$

$$P(y = 1) = \sigma(w.x + b) = \frac{1}{1+e^{-(w.x+b)}} \tag{3}$$

$$P(y = 0) = 1 - \sigma(w.x + b) = 1 - \frac{1}{1+e^{-(w.x+b)}} = \frac{e^{-(w.x+b)}}{1+e^{-(w.x+b)}} \tag{4}$$

$$\hat{y} = \begin{cases} 1 \text{ if } P(y = 1|x) > 0.5 \\ 0 \text{ otherwise } /(1 - P) \end{cases} \tag{5}$$

Then, z passes through the sigmoid function $\sigma(z)$ to calculate the probability. In the second step, a decision is made based on a threshold or decision boundary. As shown in Equation (5), the threshold is 0.5, which means if the probability of y being a member of the class is higher than 0.5, then y is a member of the class. Otherwise, y is not a member of the class. $\hat{Y}$ is *Bernoulli* distribution, and *logit*—log of odd— links the input observation with Bernoulli distribution to decide the class.

An algorithm such as gradient descent is used to minimize the distance between the estimated output and true output to learn the vector of weights and bias terms. The distance is called the *loss function* or the *cost function*. The cost function that is commonly used for logistic regression is the *cross-entropy loss function*. Unlike the linear regression, in which the mean squared error between $\hat{y}$ and y defines the loss function, conditional maximum likelihood is used for logistic regression. The likelihood of correct labels of training data defines the loss function.

The logistic regression goal is to maximize the likelihood—log probability—of the correct *y* class estimation labels given the observations *x* to choose the *w* and *b* parameter. From an optimization perspective—minimizing the loss function—, the process results in the negative log-likelihood, which is also called cross-entropy loss. Equation (6) to Equation (10) shows how to formulate the cross-entropy loss. The gradient descent approach is used in logistic regression to minimize the cross-entropy loss function and choose w and b parameters.

$$p(y|x) = \acute{y}^{y}\left(1 - \acute{y}\right)^{1-y} \tag{6}$$

$$\log p(y|x) = \log\left[\acute{y}^{y}\left(1 - \acute{y}\right)^{1-y}\right] = y \log \hat{y} + (1 - y) \log\left(1 - \acute{y}\right) \tag{7}$$

$$L_{CE}(\hat{y}, y) = -\log p(y|x) = -[y \log \hat{y} + (1 - y) \log(1 - \hat{y})] \tag{8}$$

$$L_{C}\ \ (w, b) = -\left[y \log \sigma(w.x + b) + (1 - y) \log\left(1 - \sigma(w.x + b)\right)\right] \tag{9}$$

$$C \quad (w, b) = \frac{1}{m}\sum_{i=1}^{m} L_{C}\ \ \left(\hat{y}^{(i)}, y^{(i)}\right) \quad = -\frac{1}{m}\sum_{i=1}^{m} y^{(i)} \log \sigma\left(w.x^{(i)} + b\right) +$$
$$\left(1 - y^{(i)}\right)l\ \ \left(1 - \sigma\left(w.x^{(i)} + b\right)\right) \tag{10}$$

3.2.1. Penalized logistic regression (Lasso)

The *penalized logistic regression* adds a regularization term to the objective function of the optimization algorithm—gradient descent—to penalize large weights [30]. This selection method helps resolve the overfitting and also the curse of dimensionality [30]. There are two common regularization terms—a linear function of weighted value *L1* regularization—*Lasso*—and *L2* regularization—*Ridge* [30]. *L1* regularization is selected for this study since its suitable for feature selection and deal with the curse of dimensionality—refer to section 4.5.1.1. This study uses *glmnet* r package [35] to implement lasso logistic regression. The following explains how *glmnet* computes the regularization path for lasso logistic regression[3].

The response value is either *0*—failed campaign—or *1*—successful campaign. Equation (11) shows the binomial model, and Equation (12) represents the logistic transformation of the binomial model. A negative binomial log-likelihood is used for the objective function of the penalized logistic regression, as shown in Equation (13). α and λ parameters, respectively, control the elastic-net and the overall strength of the penalty. The elastic-net affects the selection process. If α is *1*, model tends to select features that represent the lasso or *L1* regularization. For ridge or *L2* regularization, α is equal to zero. Any value of α between *0* to *1* represents a combination of these regularizations.

$$P_r(G = 1|X = x) + \frac{e^{\beta_0 + \beta^T x}}{1 + e^{\beta_0 \beta^T x}} \tag{11}$$

$$l(\quad \frac{P_r(G=1|X=x)}{P_r(G=0|X=x)} = \beta_0 + \beta^T x \tag{12}$$

$$\min -[\frac{1}{N} \sum_{i=1}^{N} y_i(\beta_0 + x_i^T \beta) - \log\left(1 + e^{(\beta_0 + x_i^T \beta)}\right] + \lambda[(1 - \alpha)||\beta||_2^2/2 + \alpha||\beta||_1] \tag{13}$$

3.3.1.1. Cross-validation

The effect of the α parameter is explained in section 3.2.1, and α is equal to *1* for this study. λ is another parameter that affects the regularization process. The path for lasso regularized regarding different values for λ represents various levels of trade-offs

[3] https://web.stanford.edu/~hastie/glmnet/glmnet_alpha.html#log

between *bias* and *variance* based on the number of selected features. Lasso, in general, prefers bias over variance by selecting features. However, a cross-validation approach is utilized to select λ parameters that balance these two factors. *Cross-validation* aims to find λ value that minimizes the variance [36]. In k fold cross-validation, the analysis is done k times. Each time, data is divided into k equally sized folds. *K-1* folds are used to train the model, and the remaining fold tests the model's performance.

3.3.1.2. Bootstrap

The *bootstrap* is the process of repeating the same analysis multiple times. Bootstrap is used to stabilize the model and assess the statistical properties of complex estimators [36]. The bootstrap replicates the cross-validation process to perform the classification model based on different training and test data sets for assessing the statistical properties [36]. The following shows the bootstrap process.

i. Fit a lasso path over a grid of λ values.

ii. Perform K fold cross-validation.

iii. Average the mean-squared prediction error over the grid of λ.

iv. Find λ that minimizes this error and return coefficient of a fitted model in step *1* for best λ.

3.3. Glossary

Direct dependency: as shown in Figure 1 one word directly depends on another if there is no other word in their dependency path or both depend on the third word [29].

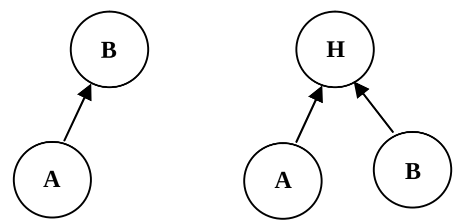

Figure 1- Direct dependency between words A and B [29].

Indirect dependency: as shown in Figure 2 one word indirectly depends on another if there is an additional word in their dependency words or both on the third word through the additional word. [29]

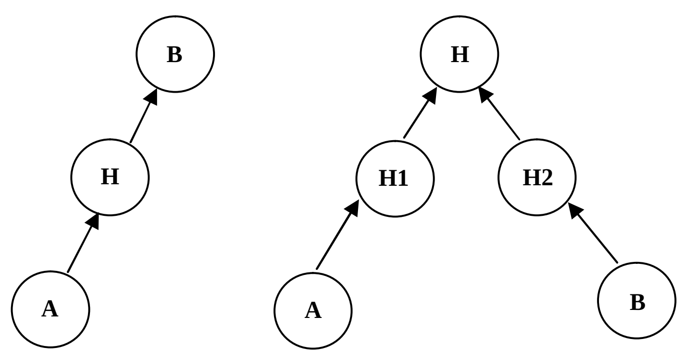

Figure 2- Indirect dependency between words A and B [29].

subjective features: subjective feature or opinion feature is a feature associated with opinion. [28]

Non-subjective features: non-subjective or objective feature is a feature not associated with opinion. [28]

Universal dependencies: "an inventory of dependency relations that are linguistically motivated, computationally useful, and cross-linguistically applicable."

Universal dependencies: binary relations that define the role of the dependent word concerning the headword in the head-dependent pair.

4. Research Design

The research design in this study consists of three major parts. The first part discusses acquiring data—section 4.1—, preparing the quantitative and textual data, and checking the reliability and credibility of the data preparation process—section 4.2 and 4.3. The second part uses the outcome of part one to build a classification model to answer research questions—section 4.4. The final part is for ensuring the validity of the model and generalization of findings at various levels—section 4.5. Figure 3 illustrates the research design process where the gray area's focus is on the model building efforts and the red area is on the validation and generalization.

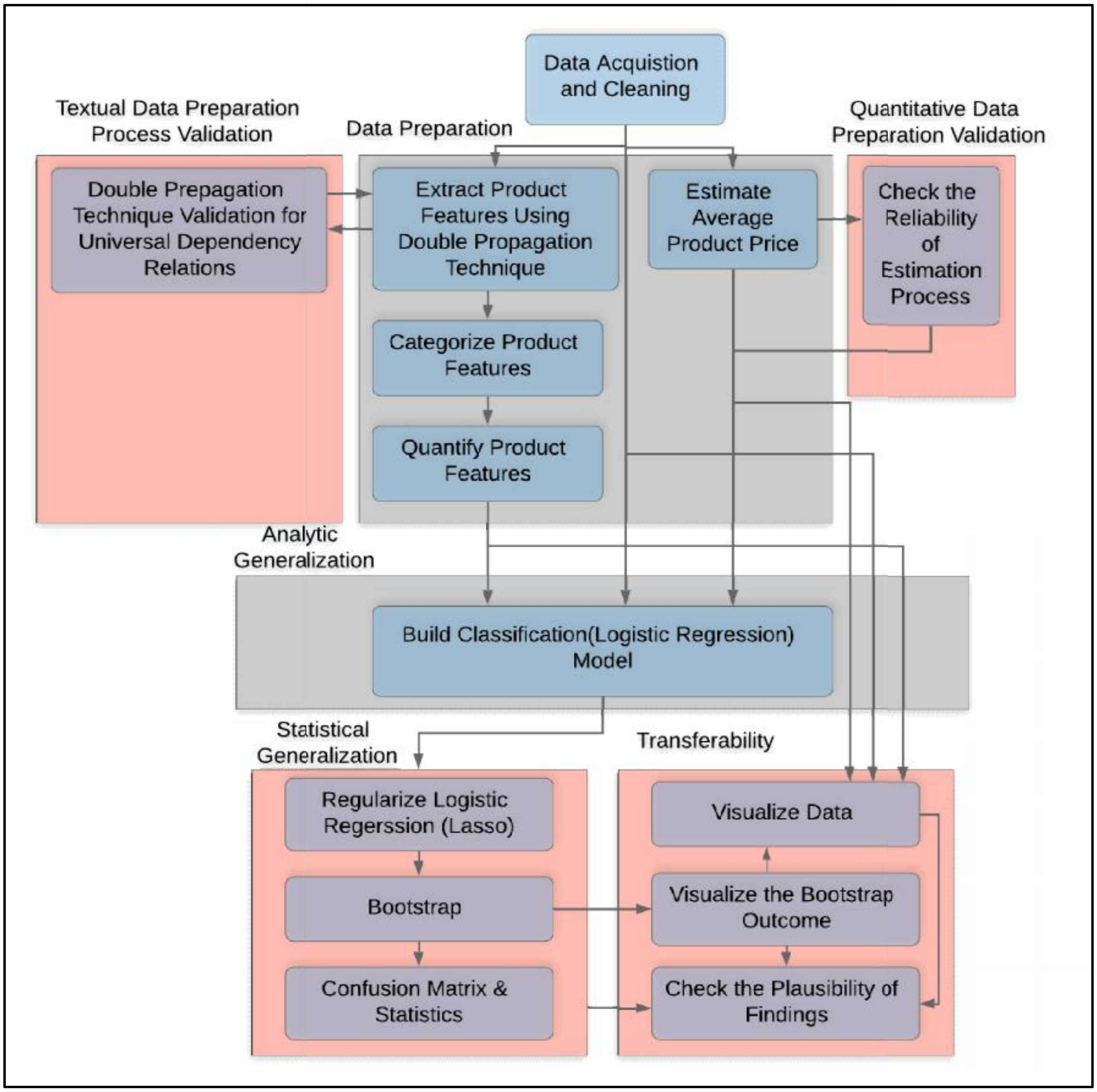

Figure 3 - Research design diagram.

4.1. Data extraction

The data are gathered for 3D printing technology from the Kickstarter platform from April 1st, 2011 to September 15th, 2017. The data was gathered using web scraping Python package—Selenium. More details on the process is given in Appendix B. The search term "3D printer" is used to identify relevant projects on the Kickstarter website. Then URLs are collected and used to open each project's campaign page and acquire information. Following information was used in this study:

- the name of project (Name),
- the concise explanation about the project (Abstract),
- the money unit considered for the project (Currency),
- the amount of money contributed to the project's campaign by supporters (Amount pledged),
- the amount of money set as a goal for the campaign (Goal),
- information provided about the campaign (Description), and
- the start date of the Kickstarter campaign (Start date)

As of September 15th, 2017, 519 projects related to 3D printing technology are identified with a known outcome that had completed their campaign. However, only projects that offer a 3D printer as a device are suitable for the purpose of this study. Therefore, the gathered projects are filtered, which is done manually based on the projects' summary. The eliminated projects can be grouped as follows:

- the projects which develop 3D printers' part such as extruder and nozzles or input materials (filaments),
- the projects which make products utilizing 3D printing technology, and
- the projects which aimed to raise money to acquire technology for various purposes.

From 519 projects, which are initially gathered, only 256 of them are offered the whole 3D printer technology and are directly related to the purpose of this study. The 256 remaining projects are then checked for duplication. Removing the duplicated projects left 244 projects for the analysis.

4.2. Quantitative data preparation

The price of a product is one of the factors studied in this work. However, it is impossible to extract the price of the product directly from the campaign page due to various reward tiers. This section elaborates on how to estimate the average price of the products and perform sensitivity analysis to understand the effect of the appreciation rewards on the estimated average price.

4.2.1.The average price of the product

Different tiers of rewards with a certain limit can be set for each project. When the limit is reached, the rewards tier will no longer be available for backers to select and would be marked as sold out. It is impractical to use a direct product price available on the project page due to various levels of rewards and product feature combinations. Instead, the estimated product price is used in the analysis. Along with the product features, price affects the relative advantages of the product.

The product price is estimated by dividing the pledged amount by the number of backers for a given product. Product estimation is formulated in Equation (14). *p*, *pa*, and *nb* represent the product price, pledged amount, and a number of backers, respectively. And *es* and *i* subscription stand for estimated and the given project, respectively.

$$p_{e,i} = p_{i}/n_{i} \tag{14}$$

4.2.2.The average price of product validity

Reward sections of technology products usually are either in the form of appreciation—material and non-material—or various product packages. In this study, some of the gathered 3D printer projects are further examined to test the effect of small pledges with appreciation return on the estimated average price of the product. Fifteen projects are selected randomly and examined to cover the price at various ranges and include the successful and failed campaign. One project out of 15 doesn't have any appreciation reward. For the rest, the pledge amount with appreciation reward range from $0.70 to $45. Also, two projects provided rewards that did not include the whole 3D printer solution, such as print material and upgrade options at a lower pledge amount.

Removing the appreciation pledge money and the associated number of backers cause the estimated average price of the product to increase. The reason is that the sum of pledged money in return for appreciation is low and barely affects the accumulated pledged amount for projects. However, removing the backers has a significant effect on decreasing the number of backers, which led to an increase in the estimated average price of the product. The changes for the high-end price is around $400 and for the low-end price is around $30. The effect of error in price estimation on the result of the classification model is further explored in section 5.2.4.

4.3. Textual data preparation

This study focuses on understanding the role that product features play in motivating backers to support crowdfunding projects. However, product features are ingrained in textual information available on the crowdfunding campaign page, and they need to be extracted before including in any model. Textual data preparation refers to a semi-automated process that includes product features extraction, categorization, and quantification. Utilizing aspect extraction techniques—well-established for customer reviews—has advantages, including faster process and more comprehensive extracted product features than other approaches such as ontology-based text mining, which depends on subject matter experts knowledge. This section elaborates on the preparation process and how the reliability of aspect extraction techniques is ensured while utilizing them in a new context.

4.3.1. Textual data preparation reliability

In this study, the textual data preparation process is similar to those used on the customer reviews. However, the process must be modified based on the differences between customer reviews and the Kickstarter dataset to ensure reliable outcomes for extracted product features and analysis in general. This section discusses the differences and outlines the required modification for this new application. Also, it briefly mentions the process that has been taken to modify the techniques for a new application.

4.3.1.1. Differences between customer reviews and Kickstarter information

This study's research process is based upon past research, which used customer reviews as the text source. Still, there are several differences between Kickstarter information and customer reviews, as highlighted in Table 6. These differences then require some modifications to the research process.

Customer Review	**Kickstarter**
There is an abundant amount of customer reviews.	Kickstarter projects are limited.
Customer reviews are usually short.	Kickstarter information is lengthy.
Customer reviews reflect users' opinions.	Kickstarter information describes the founders' opinion and technical characteristics of a product.
Provide an opinion on existing and established products.	Information is provided on products that are either do not exist or provides unique characteristics that cannot be found in the market.
All the products are available at the same period of time.	Products aren't available around the same time.

Table 6 - Comparing customer review and Kickstarter information datasets and their dynamics.

The main differences are who provides the information, experience with the product, the scope of covered features, and the emphasis on them. Using the opinions of consumers who have experience with the product introduces only modest biases in the analysis. Legitimate reviewers will typically be trying to provide a balanced perspective of the product. Harsh cynics may roughly balance extremely positive biased reviews by obsessive fans. In contrast, the information in a Kickstarter campaign is typically supplied by the founder for marketing purposes with a clear intent of “selling” the audience on the product. Therefore, the text of the Kickstarter campaign regarding features would be expected to have a systematic positive bias. So, the opinions toward the product, e.g., "affordable" and its features, are not included in the analysis. Due to the curse of dimensionality discussed in section 4.5.1.1, not all the product features can be utilized in the model.

Customer reviews are fairly short but abundant, which makes the frequency—indispensability of product aspect—an efficient method to deal with dimensionality issues discussed in section 4.5.1.1. In contrast, Kickstarter information is lengthy but limited to just the one provided by the founder. Thus the dimensionality becomes a problem. Categorization is used for aspect resolution—resolving the variation in conveying the same opinion on a given aspect of the product—in customer reviews. In this study, categorization of product features is not only used for aspect resolution but also to group the features based on their functionality for managing dimensionality. Besides, the feature selection technique—lasso logistic regression—is further utilized to deal with the limited number of cases. At last, the difference in the availability pattern of products affects how the findings are interpreted. The significant features in customer reviews reflect their essentiality and quality comparison, while the significant aspects in crowdfunding products show their desirability and novelty.

Unlike the first three differences that require modification to the product features extraction process, the last two differences in Table 6 need a different approach to interpret the results. In the general market, the products are available simultaneously making it possible for customers to compare the opinion toward the products and select the most suitable ones for their needs. In contrast, products are available on the crowdfunding platform for a very limited time, and there is no prior experience with the products. So, the assumption is that the products have unique characteristics that incentivize the backers to risk and support a project on the crowdfunding platforms. This study further examined this assumption.

4.3.1.2. Adjusting aspect and feature extraction process for crowdfunding textual information

There are some changes required to adjust the established textual information preparation process for this study. Section 3.1.2.2 explains how the dependency relations considered for product aspect extraction in double propagation [29] are replaced by universal dependency relations. This replacement enables the double propagation implementation utilizing *UDPipe* r package. The performance of new rules is checked—refer to Appendix C—to measure the appropriateness of new rules and the effectiveness of each rule in this study—crowdfunding context.

The overall performance of double propagation in capturing product features and canceling the noises are analyzed—details are elaborated in Appendix D. The double propagation technique is well suited for extracting product features. It does remove noises for the most part, but not all of them. The presence of noise is troublesome for automating the categorization. Although, it is not an issue in this study since the categorization is done manually. These two steps are essential to ensure the credibility and reliability of the data preparation process and consequently the generalization of findings.

4.3.2. Preprocessing

Preprocessing of text for the feature and opinion mining is explained in detail in section 3.1.1. Overall, preprocessing efforts can be classified as cleaning the text and reshaping input text for a given analysis. The necessary cleaning processes for text analysis in this study consist of spell-checking, unifying word variation, and replacing negations with antonyms. In comparison, required reshaping processes consist of tokenization, part of speech tagging, dependency relation, and syntactic analysis. Spell-checking, negation replacement, and tokenization are the processes to prepare corpus for POS tagging. POS, dependency grammar analysis, and lemmatization are the course of action to prepare corpus for information mining.

One of the cleaning steps is spell-checking, although the result of spell-checking is not ideal in this case. Two python packages have been tried to do spell-checking—*textblob* and *enchant*. After examining the result of the *textblob* spelling check on the few texts, it has been realized that the result is not reliable and even the correctly spelled word replaced by the wrong spelling. For instance, it changes the correctly spelled word "affordable" to "unfordable." The *enchant* result is more reliable than the *textblob*.

However, mostly detected erroneous words are the proper name. Based on the chosen dictionary—US English or British English—correctly spelled words in US English can be seen as erroneous by using a British English dictionary or vice versa. So, it seems the spell-checking is not a practical cleaning step in this case. It is essential to know to what extent skipping the spell-checking would affect the accuracy of part of speech result. It is demonstrated that spelling errors only reduce POS-tagging performance by 0.23% [37]. As it is concluded, skipping the spell-checking step won't have a significant effect on the integrity of POS-tagging analysis.

Another cleaning step for preparing data for POS-tagging analysis is replacing negation with antonyms. This achieved by replacing all the contraction form of "\'nt" with "not," and then using *WordNet* to substitute negation with antonyms. *RegexReplacer* and *AntonymReplacer* Python class from the replacers module [38] have been used to accomplish these two tasks. More information on how these two classes work can be found at [39].

The corpus is reshaped using the *UDPipe r* package. *UDPipe* is an end-to-end *"open-source tool which automatically generates sentence segmentation, tokenization, POS tagging, lemmatization, and dependency parsing tree"* [40]. Deploying learning algorithms in *UDPipe* such as Gradient Recurrent Unit (GRU) network, feature averaged perceptron, neural network classifier makes the pipeline trainable. Training and use case details for *UDPipe r* are available on *Github*[4]. Also, *UDPipe* baseline system is elaborated in [40], [41].

[4] https://bnosac.github.io/udpipe/docs/doc2.html

4.3.3. Candidate features and opinion extraction

There are four main approaches to extract explicit aspects—features— of product from unstructured text, including frequent nouns, syntactic relations, supervised learning, and topic modeling. As discussed in section 3.1.2.1, this study chooses a rule-based approach—double propagation based on syntactic relations—to extract aspects. This study follows Qiu et al. [29] bootstrapping techniques—double propagation— along with defined rules of syntactic relations to propagate features and opinion sets. Propagation carried out in four steps as follows:

i. Extracting features using opinions.
ii. Extracting features using extracted features.
iii. Extracting opinions using extracted features.
iv. Extracting opinions using both extracted and seed opinion

The bootstrapping techniques and syntactic dependency relations rules, as explained in section 3.1.2.2, are implemented in *r*. The dependency of nominal subject features is parsed using the *UDPipe r* package. Then noun phrases that contain candidate nouns and adjectives are identified using noun phrase extractor from the *UDPipe* package. The noun phrase patterns for product aspects are as follows: *NN*, *NN NN*, *JJ NN*, *NN NN NN*, *JJ JJ NN*, where *NN* and *JJ* are noun and adjective, respectively [42]. Overall, 22660 candidate product features are identified and used to find associated noun phrases.

4.3.4. Product feature categorization

In customer reviews, the aspect of products and opinions towards them are often written in different ways. For example, the set of words *price*, *cost*, and *expensive* and the set of words *picture*, *image*, and *photo* refer to price and image aspects of a camera, respectively. The process of grouping or clustering of aspect expressions into aspect categories is called entity or aspect resolution [31]. There are various approaches for aspect resolution like dictionary-based clustering, using *WorldNet* to define similarity metrics [43], semi-supervised learning approach [44], a multilevel latent semantic association based on Latent Dirichlet Allocation (LDA) [45], and Constrained-LDA [46].

However, in this study, associating the product features to a broader category purpose is not limited to entity resolution. As explained in section 4.3.1.1, categorization is also aimed at reducing the dimensionality of product features based on their functionality. So, categorization is more knowledge-based rather than word similarity either semantically or structurally. Therefore, the categorization process cannot be fully automated using approaches like LDA and hierarchical agglomerate clustering. The rest of this section elaborates on the categorization process and discusses the reliability of the process.

4.3.4.1. Categorization process

A semi-automated approach is used to categorize extracted features for 3D printers. This approach combines a hierarchical agglomerate clustering approach with expert knowledge to categorize the product features into broader categories. Figure 4 shows four steps of the text process—clustering similar phrases, extracting key technologies, characteristics, systems, and processes, grouping them into main characteristics, and product feature categorization. The last two steps are text preprocessing and the main categorization process.

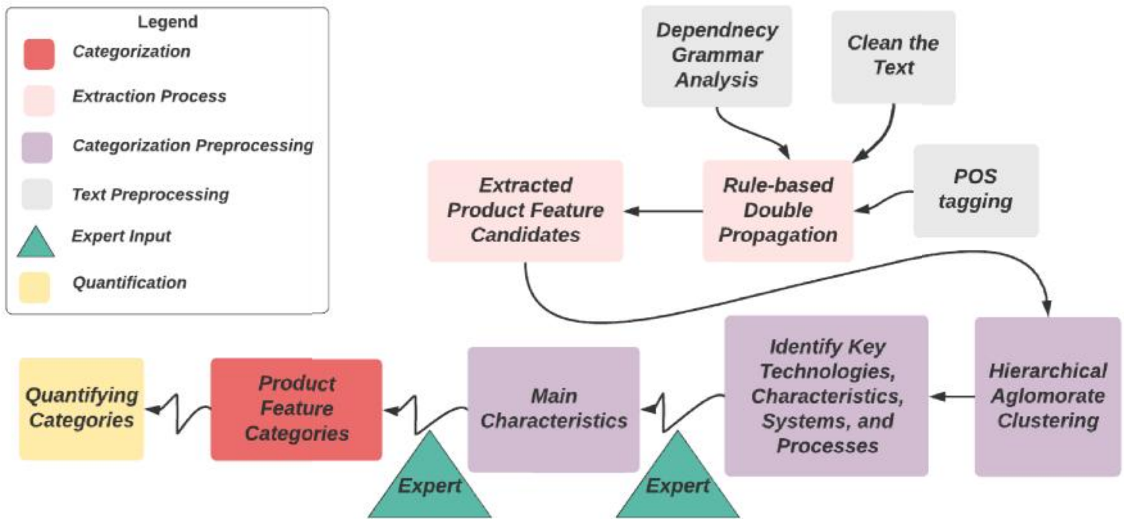

Figure 4 - Text processing path

Clustering similar phrases: Hierarchical agglomerate clustering is utilized to grouping similar phrases to facilitate identifying the key technologies, characteristics, systems, and processes. The number of clusters defines the refinement of each cluster to some degree. Increasing the number of clusters after a certain point doesn't improve the distinctiveness of some of the clusters, so a separate additional clustering process is applied in these cases.

Extracting key technologies, characteristics, systems, and processes: Figure 5 and Figure 6 are two examples of hierarchical agglomerate clustering results. The first cluster points to composite filament technology, and the second cluster represents the extruder system. These clusters are not the only ones that include these two features. However, they are enough for these key technologies' identification. Besides, not all the phrases are meaningful in the cluster, but this is not a concern at this stage.

```
$`63`
[1] "composite filaments"           "specialty composite filaments" "composite filaments.from"
[4] "tech composite filaments"      "many composite filaments"      "new composite filaments"
[7] "abrasive composite filaments"  "complete filament"
```

Figure 5 - Composite filament category

```
$`24`
 [1] "dual extruder"       "dual extruders"      "paste extruder"      "single extruder"     "second extruder"
 [6] "head extruder"       "new extruder"        "metal extruder"      "style extruder"      "hot end extruder"
[11] "end extruder"        "drive extruder"      "own extruder"        "design extruder"     "rova3d extruder"
[16] "plastic extruder"    "own extruders"       "better extruder"     "most extruders"      "future extruders"
[21] "deg c. extruder"     "c. extruder"         "clay extruder"       "most extruder"       "more extruders"
[26] "entire extruder"     "color extruder"      "cheap extruders"     "robox extruder"      "good extruder"
[31] "plastic extruders"   "use extruder"        "able extruders"      "other extruder"      "double extruder"
[36] "ceramics extruder"   "classic extruder"    "same extruder"       "pour extruder"       "robust extruder"
[41] "best extruder"       "c extruder"          "triple extruder"     "colour extruder"     "fdm extruder"
[46] "easy extruder"       "electronic extruder" "end extruders"       "titan extruder"      "paste extruders"
```

Figure 6 - Extruder system category

Grouping key technologies, characteristics, systems, and processes into main characteristics: After manually extracting the key technologies, characteristics, systems, and processes regarding the clusters, they are validated by a subject matter expert. Those key technologies, characteristics, systems, and processes are mapped into a group based on the functionality they represent. For example, the filament group only consists of one term, filament. In comparison, the material group includes many terms such as *pla*, *abs*, *plastic*, *clay*, *wood*, *composite*, and *nylon*.

Product feature categorization: The next step is to gather all the extracted phrases related to a group. For instance, all the terms that include *pla*, *abs*, *plastic*, *clay*, *wood*, *composite,* and *nylon* words are selected from extracted product features for the material group. Then those selected phrases are presented to experts for categorization. For the material group, two categories are dedicated as *composite* and *non-composite thermoplastic filament* types. However, these categories are not exclusive to the material group, and they include other phrases in other groups, such as filament.

Some of the main characteristics of a 3D printer are eliminated during the categorization process. If there is no distinguishing factor in extracted phrases for a given group that led to at least two distinctive categories, the characteristic is eliminated from the process. For example, the building area group consists of the *build area, build envelope*, *build size*, *build volume*, *print envelope*, *print volume*, *printing area*, *work area*, and *workspace*. However, one factor in distinguishing build areas from each other is the size of the area. The problem with including the size is the availability of the actual build area and the relativeness of the size. It is challenging to categorize the build area for these two reasons.

Besides, One of the categorization challenges is the case where a phrase has an ambiguous meaning. For example, a "full color" phrase can point to a 3D printer that can handle material with multiple colors. It can indicate other full-color options such as full color printed manual. A shiny app[5] is created for checking the context of phrases to provide more context. The expert can enter the term and access all sentences that have the exact phrase.

4.3.4.2. Variance and reliability of product features categories

Product features are categorized based on similar characteristics in their functionality. However, some of the defined functionalities are not mutually exclusive, and they can be merged into a broader category. Also, each category can be broken down into sub-functionalities and narrower categories. The breadth of categories affects the result of the model and findings. Too broad or narrow categories would result in no insight due to the limited size of data. Product features in each category are documented in Appendix E. As

[5] https://ninach.shinyapps.io/phrase_checker/

long as the same rules and similar functionality are considered for categorization, categorization should be comparable between this study and future research.

4.3.5. Quantification

Qualitative data, including text, needs to be quantified to be suitable for models such as regression. *Binominal Document-Term Matrix* is used to quantify defined categories. In this case, the matrix row illustrates the 3D printer project—document—and the column represents the categories—term. The value of each cell is either *0* or *1*. *0* shows that the category is not present in a given project, and *1* shows that the category belongs to a given project. Figure 7 provides an example of a document-term matrix with five projects and three categories: price, quality, and accuracy. The matrix shows various scenarios. The first project has two categories—Quality and Accuracy—, the second project has no category, the third project only has a Price category, the fourth project has all three categories, and the fifth project only has a Quality category. The "TermDocumentMatrix" function from the tm r package [47] is used to build a matrix to quantify the features and opinion categories.

$$
\begin{array}{c c}
 & \begin{array}{ccc} P & Q & A \end{array} \\
\begin{array}{c} P1 \\ P2 \\ P3 \\ P4 \\ P5 \end{array} &
\begin{bmatrix} 0 & 1 & 1 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix}
\end{array}
$$

Figure 7 - example of document-term matrix.

4.4. Classification model to capture the effect of product features on the success of the campaign

The objective of the classification model is to explore the desirability of new designs in this work. This study intends to evaluate the deriving power of product features in the success of the crowdfunding campaign. This is an improvement to the previous model in which mainly campaign features are considered influential factors in the crowdfunding campaign's success. Campaigns—dependent variable—are classified into successful and failed classes regarding product features utilizing logistic regression. Equation (15) represents the logistic regression where *i* refers to an *i'th* campaign, s_i is a categorical variable with two categories—successful and failed—, d_i shows the general interest in product regardless of product features, X_i represents the vector of quantified textual product feature variables, β_i^x represents the coefficient for product feature *x*, and $\mathcal{E}_i$ shows the estimation error.

$$\log\,(s_i) = d_i + X_i\beta_i^x + \varepsilon_i \tag{15}$$

Including textual information in the model decreases the ratio of the amount of information N per parameter P. In case $P > N$—the curse of dimensionality—, an infinite set of the solution makes the least-square function equal to zero [36]. In this scenario, the only subset of parameters is non-zero, and parameter estimation is effective if the true model is sparse [36]. The classification model, in this work, is considered sparse since the assumption is that crowdfunding products are innovative and scarce. Actual non-zero parameters are estimated by adding a penalized term to logistic regression—applying Lasso logistic regression shown in Equation (16).

$$\log(s_i) = d_i + X_i\beta_i^x + \varepsilon_i + P \tag{16}$$

Lasso logistic regression overcomes the curse of dimensionality by forcing some of the coefficients of the independent variables to zero and reducing the model dimension. The curse of dimensionality and dimensionality reduction is further discussed in sections 4.5.1.1 and 4.5.1.2, respectively. Moreover, cross-validation and bootstrap are implemented—further discussed in sections 4.5.1.3 and 4.5.1.4—to improve parameter estimation and generalizability of the model. The followings are the steps taken to estimate classification model parameters. Lasso logistic regression is fitted using *glmnet r* package [35].

i. Fit lasso logistic regression over a grid of $\Lambda = \{\lambda_l\}_{l=1}^{L}$. Figure 8 shows an example of fit over a grid of Λ where $log(\lambda) \epsilon [-2, -9]$. The *x*-axis at the top represents the number of non-zero coefficients associated with each $log(\lambda)$.

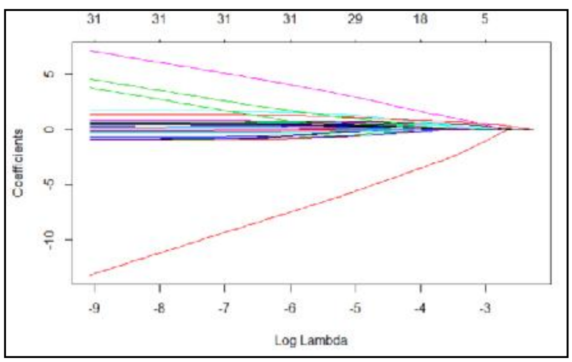

Figure 8 - Example of lasso logistic regression fit over a grid of $\Lambda = \{\lambda_l\}_{l-1}^{L}$.

ii. Divide the data into 10 equal folds at random.

iii. Use 9 folds as training data and fit lasso logistic regression using the same grid Λ in step i.

iv. Use remaining fold—10th fold—as test data to calculate mean-squared prediction error for each $\lambda \in \Lambda$.

v. Repeat steps iii and iv 10 times and average mean-squared prediction errors to obtain prediction error curve over grid Λ. Figure 9 shows an example of a prediction error curve over a grid of Λ where $log(\lambda) \in [-2, -9]$. The x-axis at the top represents the number of non-zero coefficients associated with each $log(\lambda)$.

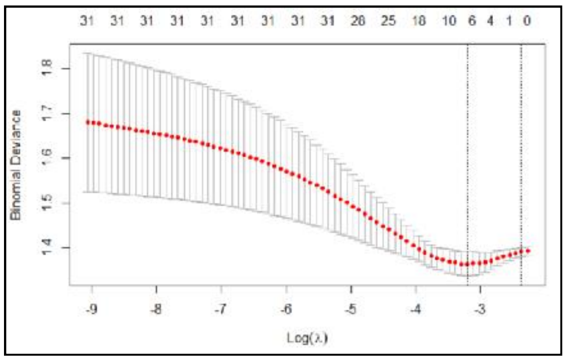

Figure 9 - example of prediction error curve over grid Λ.

vi. Find the best λ that minimizes the error curve and return the coefficients from fit in step i for best λ—Figure 10 shows an example of the parameter estimation process. These coefficients will be used to visualize the coefficient changes over bootstrap samples, as discussed in section 4.5.1.4.

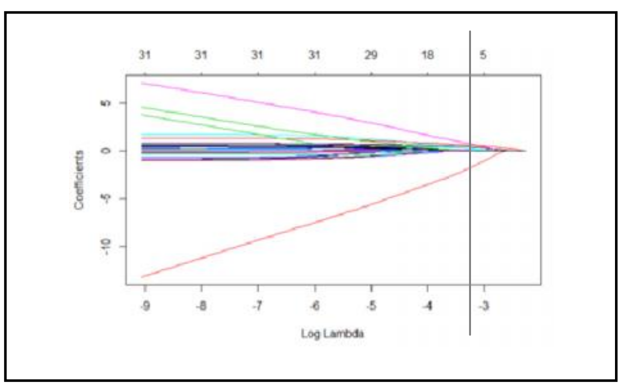

Figure 10 - example of coefficients selection for best λ for fit in step 1.

vii. Repeat steps ii through *vi* 100 times—bootstrap, calculate the average of average mean-squared prediction errors in step v and find best λ with minimum error.

viii. Return the coefficients of fit in step *1* for best λ.

ix. Compare the model's performance from step viii with the model obtained from λ that selects the same number of parameters with the negligible prediction error difference with best λ to determine the optimal λ.

Fundamental features of 3D printers vary based on the processes used to print objects—refer to section 5.1. Considering all the processes in one classification model worsens the dimensionality issue. Although there are similar aspects such as software and device interface between 3D printers use different processes, the essential features are vastly different and not comparable. So, the analysis has been conducted for each process separately.

The goal of the classification model is to analyze the impact of product features on the success of the campaign. The model presented in Equation (16) takes into consideration only the effect of product features. However, like other innovations, other factors, including time and price, impact the desirability and demand of the product. To factor in the effect of time and price, projects are segmented based on time, price, and combination of time and price. Then classification model—Equation (16)—is applied to each segment's projects.

The performance of the classification model is evaluated using the *confusion matrix* and *statistics* discussed in section 4.5.1.5. The confusion matrix shows the number of correctly and incorrectly predicted cases for each class—successful and failed campaigns.

P-value in confusion statistics provides the confidence level for the accuracy improvement in outcome prediction by including product features in the model. Moreover, McNemar's test *p*-value shows the significance of imbalance in false success or failure predictions.

4.5. Model validation

The quality and value of the model are evaluated based on its *reliability*—stability of findings—, *validity*—truthfulness of findings—, and *generalizability*—extrapolate findings to unobserved situations and times [47], [48]. However, validity and generalizability are interrelated, where generalizability is often referred to as external validity versus internal validity that focuses on the degree of confidence in the tested relations [49]. These quality evaluation criteria are rooted in quantitative research and often represent controversy and challenges for qualitative research. This study uses quantitative methods, however, it faces the same challenge as qualitative research to make inferences—external validation.

Three generalizability models are considered for quantitative and qualitative studies—*statistical generalization*, *analytical generalization*, and *transferability* [50]. Statistical generalization is mainly applied in quantitative research in which the interest is to extrapolate from a sample to a population. Analytical generalization model is used both in qualitative and quantitative, an evidence-based approach to support general concepts or theories. Lastly, the transferability or case-to-case translation provides a detailed description to enable the reader to make informed inferences about the findings. This study utilizes all three generalization models to enable generalization and conceptualization with various breadth, as shown in Table 7.

Product	Crowdfunding platform	Generalizability
Technology product	Any Hedonism crowdfunding platform with a technology product category	Conceptualized patterns are generalizable through the analytic and transferability generalization model.
Technology product	Kickstarter—hedonism crowdfunding platform	Conceptualized patterns are generalizable through the analytic and transferability generalization model.
3D printer	Any Hedonism crowdfunding platform with a technology product category	All the findings are generalizable within the technological process segment.
3D printer	Kickstarter—hedonism crowdfunding platform	All the findings are generalizable within the technological process segment.

Table 7 - Generalization model utilized for conceptualization breadth according to product and crowdfunding platform.

The statistical validation—further discussed in 4.5.1—examines the standard quality of model findings and generalization for 3D printer products on hedonism crowdfunding platforms such as Kickstarter. This study also depends on analytic generalization and transferability to make inferences for technology products on hedonism platforms in general. Both generalization models rely heavily on research rigor and providing comprehensive insight into the research process to ensure quality [48]. The research rigor is measured by criteria including credibility, fittingness, auditability, dependability, relevance, plausibility, neutrality, and authenticity [51]–[53].

The credibility of analysis is ensured through reliable and auditable data preparation processes and statistical validation of the classification model. First, it is checked if the average cost of engagement represents the average value of the product—refer to section 4.2.2. The next step is ensuring the reliability of the textual information extraction process by adjusting the extraction techniques for the crowdfunding context. Product feature extraction processes are mainly developed for customer reviews. The process is adjusted based on the difference between customer reviews and crowdfunding context discussed in section 4.3.1.1 and section 4.3.1.2. Besides, automatic extraction of product features increases the reliability of capturing comprehensive aspects of the product rather than relying solely on the knowledge of an expert. Product feature categories—defined by subject matter expert— and the phrase included in each category are documented in Appendix E for auditability purposes. Credibility of the classification model is further discussed in section 4.5.1.

The fittingness or proximal similarity in the forms of time, people, settings, and contexts defines the dependability and transferability of the findings. This study limits the generalization of findings to technology products on hedonism crowdfunding for fittingness purposes. Tech-savvy people have a higher chance of showing similar behavior on hedonism crowdfunding than backers who support music, art, game, etc. Furthermore, the validity of truthfulness is challenged in complex systems due to limited understanding. Consequently, it is recommended to focus on usefulness rather than truthfulness for the complex problem at hand [54]. Data availability for every crowdfunding technology product is not necessarily as rich as a 3D printer, so it is impossible to conduct a similar analysis for each technology product on a crowdfunding platform. Thus, it is helpful to learn from similar technology products and transfer the relevant knowledge to new settings. This study intends to conceptualize the effect of product features, time, and price on the campaign's success—demand of the product. Section 4.5.2 elaborates the steps to ensure the plausible, neutral, and authentic findings by providing a detailed description of product feature trends through visualization, subject matter expert inputs, and factor in the tradeoff between scarcity of product features and dimensionality reduction as part of statistical validation.

4.5.1. Statistical validation

The reliability of the classification model depends on the reliability of the input data, which is discussed in section 4.5. This section focus on the reliability and validity of the model results. The curse of dimensionality causes overfitting and accuracy issues for the classification model—further discussed in section 4.5.1.1—which are alleviated by applying lasso logistic regression to reduce the dimension by selecting fewer features—refer to section 4.5.1.2. Cross-validation is used to optimize the lasso performance, as discussed in section 4.5.1.3. The model result is stabilized using the bootstrap technique, and model performance is evaluated through confusion matrix and statistics, respectively discussed in 4.5.1.4 and 4.5.1.5.

4.5.1.1. The curse of dimensionality

The curse of dimensionality (CoD) issue is a known problem in the regression model with the textual variables. Classification model considering textual information involves analyzing data in high dimension space since each word or term represents a dimension. Analysis in high dimensions can easily be cursed. There are two issues associated with CoD.

First: The sparsity of data is one of the issues associated with the curse of dimensionality. As dimension grows, the number of data or observations should grow exponentially to fill the space. Thus, a relatively high number of variables compared to the number of observations is considered sparse with a high variance that causes overfitting and statistical significance issues.

Second: the closeness of data is the second issue associated with CoD. Data points may seem further from each other and dissimilar in a higher dimension than lower dimension space. This issue arises in sorting or classifying data where inferences are made based on data similarity and distances. In a high-dimension environment, the distance between points converges to the same value, and random variations obscure real differences. The distance concentration negatively affects the accuracy of classification.

4.5.1.2. Dimensionality reduction

The feature selection is an approach to solve the CoD problem. The feature selection method reduces the dimension of explanatory variables through the selection process. *Filter* methods, *wrapper* methods, and *embedded* methods [55] are three common feature selection methods. Filter methods rank and choose the features based on their usefulness. Wrapper methods create subsets of variables, and the best subset gets selected by testing the model. And embedded methods are the combination of the first two methods. Lasso regression is the embedded method where the insignificant variant variables are regularized and shrink to zero while minimizing the estimation error. Lasso regression controls the strength of regularization by tuning the λ parameter. Bigger λ forces more variables coefficient shrinks to zero.

4.5.1.3. Cross-validation

Lasso controls the complexity of the model using the λ parameter. Higher values of λ restrict parameters, select fewer parameters, lower the model complexity, increase its interpretability, and decrease the model goodness-of-fit. In reverse, lower values of λ give more flexibility to the model to adapt more closely to training data. A grid of λ is used to monitor the performance of Lasso. Too small λ leads to *overfitting,* and too large λ leads to *underfitting*. The best λ is the one that minimizes the mean estimation error.

Cross-validation is an approach to find *optimal* λ. In cross-validation, data is divided into *k* equally sized subset or folds. *K-1* folds are used to estimate the model, and one fold is held out to test the model's performance. Then, this process is repeated *k* times. Though the best λ is the one that yields the minimum estimation error, the estimation error and model accuracy are considered together to choose the optimal λ in this study. The best λ is replaced by optimal λ if the following conditions have met. If the same number of parameters have been selected, the difference between error estimation and estimation error of best λ is negligible, and model accuracy is better.

4.5.1.4. The bootstrap

The bootstrap technique is used to stabilize selection output and provide insight for non-dominant trends in this study. The best λ chosen through cross-validation varies slightly for each run. These variations are due to the scarcity of product features and the randomness of each fold. The best λ selection stabilized using bootstrap. Besides, bootstrap shows how the product features coefficient changes over bootstrap samples. Each product features coefficient variation is illustrated by a boxplot of bootstrap realizations and the probability of non-zero coefficients in bootstrap distribution. This visualization is helpful if no feature is selected or the effect of the feature is masked by another feature.

4.5.1.5. Classification performance evaluation

Confusion matrix and statistics are used to evaluate the performance of the classification model. Confusion matrix and statistics are generated using the *caret r* package [56]. The confusion matrix and associated statistics can be used to check various aspects of the model. In this study, the positive class is always a successful class or category *1*. Table 8 shows the confusion matrix where columns are actual, or reference classes and the rows are model predictions. *A* and *D* represent the correct prediction number, while B and C show the number of incorrect predictions of a successful and failed campaign, respectively. Table 9 describes associated statistics with the performance of the classification model.

The measures in Table 9 are used to analyze two main factors in the classification model. The first factor is the confidence level for the accuracy improvement in outcome prediction by including product features in the model. The second factor is the imbalance and bias in the false success or failed prediction. The first four statistics measure the accuracy and its significance. "Accuracy" and "95% *CI*" measure the model prediction accuracy and associated confidence interval. "No information" rate shows the prevalence of the dominant class. "*P*-Value" indicates if the probability of accurate prediction of both classes is significantly better than dominant class prevalence.

"Mcnemar's test *p*-value" indicates if the model performance in one class is significantly better than another. If the test *p*-value is less than 0.1 shows that with 90% confidence, there is a performance imbalance. The rest of the measures in Table 9 provide more detailed information on performance imbalance and bias. For instance, "sensitivity" and "specificity" show how well model performance detects successful and failed campaigns, respectively. "POS Pred Value " and "Neg Pred Value" balance the effect of class imbalance of dataset in sensitivity and specificity measures. "Prevalence," "detection rate," and "detection prevalence" are assessing the success of the campaign in terms of the percentage in a dataset, the percentage of correctly predicted successful campaigns in a dataset, and the percentage of the campaign indicated to have a successful outcome, respectively. And the "balanced accuracy" provides balanced insight into model performance.

		Reference	
		Successful (*1*)	Failed (*0*)
Predicted	Successful (*1*)	*A*	*B*
	Failed (*0*)	*C*	*D*

Table 8 - Confusion matrix reference generated by *caret* package.

Positive Class: 1	
Accuracy	$(A + D)/(A + B + C + D)$
95% *CI*	a confidence interval for the probability of success.
No Information Rate	$\max\{(A + B)/(A + B + C + D), (C + D)/(A + B + C + D)\}$
P-Value *[ACC > NTR]*	testing the probability of success (accuracy) is better than no information. (binom test)
Mcnemar's Test *P*-Value	chi-squared test for checking the symmetry of probability of wrong prediction(false positive and negative).
Sensitivity	$A/(A + C)$
Specificity	$D/(B + D)$
POS Pred Value	$(\text{sensitivity} \times \text{prevalence})/((\text{sensitivity} \times \text{prevalence}) + ((1 - \text{specificity}) \times (1 - \text{prevalence})))$
Neg Pred Value	$(\text{specificity} \times (1 - \text{prevalence}))/(((1 - \text{sensitivity}) \times \text{prevalence}) + (\text{specificity} \times (1 - \text{prevalence})))$
Prevalence	$(A + C)/(A + B + C + D)$
Detection Rate	$A/(A + B + C + D)$
Detection Prevalence	$(A + B)/(A + B + C + D)$
Balanced Accuracy	$(\text{sensitivity} + \text{specificity})/2$

Table 9 - Description of confusion statistics generated by *caret* package.

4.5.2. Analytic generalization and transferability

This study uses analytic generalization and transferability approaches to extend the findings to technology products on hedonism crowdfunding platforms. Analytic generalization approach is used to explore the effect of time and price on the perceived attributes of innovation, the general concepts within the diffusion of innovation theory. A detailed description is provided, and the process is thoroughly documented for the 3D printer case to make findings transferable to other technology products. The rest of this section discusses the steps are taken for analytic generalization and transferability.

4.5.2.1. Technological process segmentation

Various process has been used to print 3D objects. For the crowdfunding projects launched as of September 15th, 2017, the processes used by 3D printers are either material extrusion or vat photopolymerization. Technological process segmentation helps with dimensionality issues discussed in section 4.5.1.1. Also, technological process segmentation highlights the differences in various product development trends and their effects on analyzing the perceived value of product features.

4.5.2.2. Time and price segmentation

The perceived value of innovation shapes the attitude and perception toward the innovation and impacts backers' decision to take further action to support a project. According to the Research Gap section discussion, relative advantages are influential attributes affecting the perceived value of innovation in crowdfunding environments that are influenced by time and price. Time and price segmentation helps to understand how product features gain, maintain or lose the advantage. Time segmentation provides insight into the change in product feature effect regarding possible product maturation. Price segmentation is helpful to understand the value of product features. Time and price segmentations show the interaction between these two effects and any counter-effect between time and price.

4.5.2.3. Descriptive visualization

Various visualization graphs provide deep insight into the analysis and help with relevant inference to other technology products. The bar graph is used for illustrating different information, including the percentage of successful and failed campaigns throughout the years, the existence rate of product features in successful and failed. Moreover, box plots and bar plots show the coefficient range and the probability of non-zero coefficient in bootstrap results per product features. The heatmap is used to indicate the co-occurrence of product features.

4.5.2.4. Product feature scarcity vs. dimensionality reduction

Product feature novelty is the main characteristic of innovation. There is a direct relation between novelty and scarcity of features. Although, the scarce nature of influential features, in the first place, makes the analysis possible through dimensionality reduction. Also, the effect of the fairly influential feature may ignore if their influence isn't as decisive of the selected features and they are not in close distance of the selected features. There is a tradeoff between the attractiveness of scarce features and confidence in their influence in a nutshell.

The selection process is analyzed concerning three parameters—frequency of feature, association strength of feature with a failed or successful project, and co-occurrence frequency with other influential features. Then, the probability of the nonzero coefficient is used to identify ignored influential features regarding the selection process. Section 5.2.6 elaborates on the selection process, scenarios that influential features were ignored, and how the tradeoff compensated for drawing meaningful findings.

4.5.2.5. Plausibility validation

The plausibility of findings is confirmed with the subject matter expert regardless of statistical validation. However, ensuring the plausibility of finding through the subject matter expert gains more importance where the probability of non-zero coefficients is used to draw insights. The source of validation is explicitly stated in section 5.2.6. The findings are labeled "verified by subject matter expert " if only utilizes the features with a non-zero probability of non-zero coefficient and feature is not selected in any analysis. The findings that are based on selected features and statistically validated are labeled as "statistically verified." The subject matter expertise in this research lies in both innovation diffusion concept and 3D printing technology.

5. Analysis and Results

This section provides the result of classification models. The analysis is segmented by the 3D printing technological processes—the *material extrusion* and the *vat photopolymerization* process. The analysis in the material extrusion process—section 5.2— is extended to time and price segmentations. In contrast, the analysis in the vat photopolymerization process—section 5.3—is limited to a general model with no segmentation due to lack of data. The results of the analysis in both processes are discussed separately. The insights are drawn from results regarding research questions stated in section 2.5.

5.1. 3D printing technological processes

There are various technology labels for 3D printing technology due to patent and trademark regulation. However, the "ISO/ASTM 52900" standard [57] considers seven categories for the additive manufacturing process, as shown in Table 10. Barnatt [58] has adopted the "ISO/ASTM 52900" classification to identify similar technologies that use the same approach to print objects. Table 11 groups the 3D printing technology label based on the additive manufacturing process uses to print objects.

3D printing Process Category	Definition
Material Extrusion	A nozzle extrudes a semi-liquid material to build up successive object layers.
Vat Photopolymerization	A laser or other light source solidifies successive object layers on the surface or base of a vat of liquid photopolymer.
Material Jetting	A print head selectively deposits droplets of a liquid build material that is cured or fused solid using UV light or heat or which solidifies on contact.
Binder Jetting	A print head selectively sprays a binder onto successive layers of powder.
Powder Bed Fusion	a laser or other heat source selectively fuses successive layers of powder.
Directed Energy Deposition	A laser or other heat source fuses a powdered build material as it is being deposited.
Sheet Lamination	Sheets of cut paper, plastic, or metal are stuck together.

Table 10 - The additive manufacturing process categories in the "ISO/ASTM 52900" standard.

All the 3D printing technologies projects launched on Kickstarter from 2011-2017 are using either the material extrusion or vat photopolymerization process. The majority of them are labeled as *FDM*, *SLA*, and *DLP*. Material extrusion is the process of extruding thermoplastic materials. Vat photopolymerization is the process that uses a light source to solidify successive layers of photopolymer on a surface or base of a vat liquid photopolymer. Figure 11 illustrates the fundamentals of material extrusion on the left and vat photopolymerization on the right.

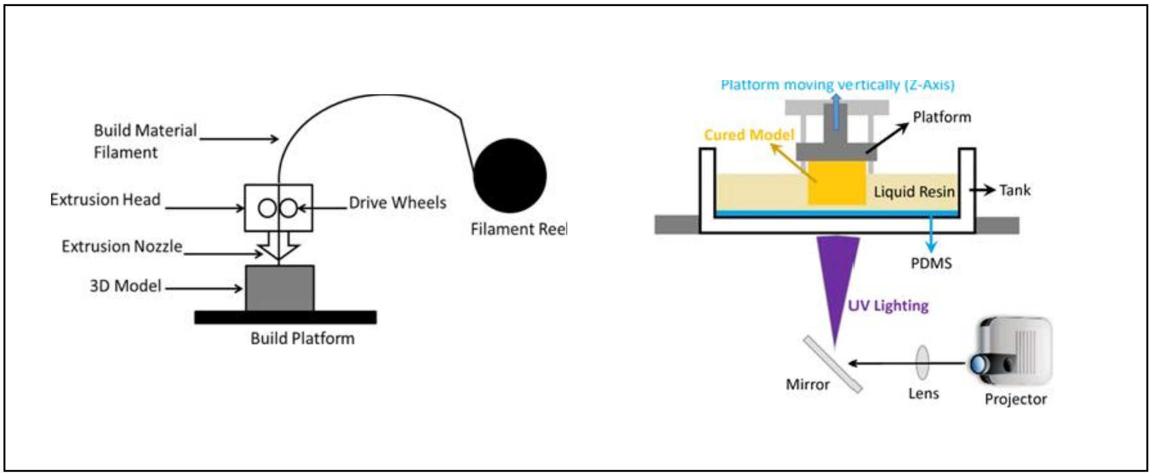

Figure 11 - The material extrusion process (on the left) and the vat photopolymerization process (on the right).

The material extrusion process uses the extrusion system to print an object from solid or paste material, while, vat photopolymerization process uses a light source to cure the liquid photopolymer. So, the 3D printing technology features using one process are vastly different from another. Considering both together will worsen the curse of dimensionality problem without having any added value. So, the analysis for each technology is carried separately.

Additive Manufacturing Process Category	Associated Technologies
Material Extrusion	FDM (Fused Deposition Modeling) PJP (Plastic Jet Printing) FFM (Fused Filament Modeling) MEM (Melted and Extruded Modeling) FFF (Fused Filament Fabrication) FDM (Fused Deposition Method)
Vat Photopolymerization	SLA (Stereolithography) DLP (Digital Light Processing) DPP (Daylight Polymer Printing) LAMP (Large Area Maskless Polymerization) 3SP (Scan, Spin, Selectively Photocure) LCM (Lithography-based Ceramic Manufacturing) CLIP (Continuous Liquid Interface Production) 2PP (Two-Photon Polymerization)
Material Jetting	PolyJet (Photopolymer Jetting) MJP (MultiJet Printing) ProJet 3D WDM (wax Deposition Modeling) DOD (Drop on Demand) Printoptical NPJ (NanoPartical Jetting)
Binder Jetting	Inkjet-Powder Printing (Z Printing) ColorJet Printing
Powder Bed Fusion	LS (Laser Sintering) SLS (Selective Layer Sintering) DMLS (Direct Metal Laser Sintering) SLM (Selective Laser Melting) LBM (Laser Beam Melting) DMP (Direct Metal Printing) LMF (Laser Metal Fusion) LaserCUSING MLS (Micro Laser Sintering) EBM (Electron Beam Melting) SHS (Selective Heat Sintering)
Directed Energy Deposition	DED (Direct Energy Deposition) LENS (Laser Engineered Net Shaping) LMD (Laser Metal Deposition)
Sheet Lamination	LOM (Laminated Object Manufacturing) SDL (Selective Deposition Lamination) UAM (Ultrasonic Additive Manufacturing)

Table 11 - Additive manufacturing process categories and associated 3D printing technologies.

5.2. The material extrusion process analysis

The majority of 3D printer projects on Kickstarter fall into the material extrusion process category. From 244 collected projects for this study, 199 projects belong to the material extrusion process category. The prevalence of the material extrusion process is mostly due to the coincidence of FDM patent expiration and Kickstarter formation and the ease of implementation of the process. Figure 12. illustrates the distribution of Kickstarter projects utilizing the material extrusion process from 2011-2017. The number of launched projects steadily increased in the first four years and plateaued in 2015 and declined in the last two years, which indicates that the material extrusion process projects reached the saturation points in 2015. The success rate of projects' campaign from 2011 to 2017 is 75%, 46.7%, 61.3%, 47.8%, 52.2%, 52.6%, 52.6%, respectively. There is more fluctuation in the success rate in the early years compared to the last three years with almost the same success rate. Although the number of launched projects has declined after 2015, the success rate has remained steady.

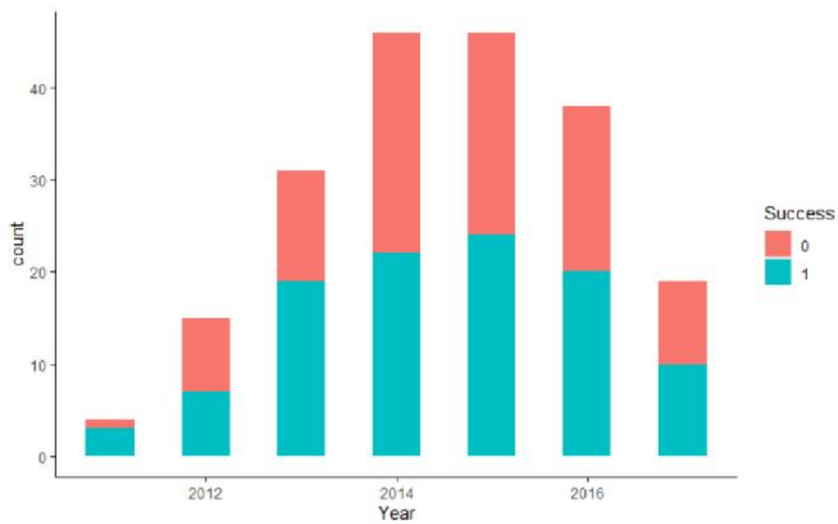

Figure 12 - Material extrusion 3D printer's project distribution from 2011-2017.

Material extrusion is the process of extruding thermoplastic materials, which is invented by Stratasys and labeled as Fused deposition Modeling (FDM). In the material extrusion process, the build material is referred to as a filament heated between 180°C and 250°C at the print head. Then, semi-solid material extrudes through nozzle layer by layer on a flat horizontal surface called build platform or print bed.

The build material for the material extrusion process can be a thermoplastic filament, wood and metal composite filament, metal, concrete, clay, and food. The most common filament is acrylonitrile butadiene styrene, a petroleum-based thermoplastic well-known as ABS. Other thermoplastic filaments are nylon and polyamides, ABS-Polycarbonate composites, and so forth. In addition to petroleum-based filaments, there is a bioplastic made from agricultural products. The popular bioplastic filament is polylactic acid or PLA. The PLA does not emit toxic fumes when heated, and it is biodegradable. There are also some efforts to reinforce filaments by adding carbon fiber, fiberglass, or Kevlar to thermoplastic materials. Other trends of filaments include electrically conductive filament and composite filament. Composite filaments combine other materials like wood and metal with thermoplastic to build a new composite like Laywoo-D3, medium-density fiberboard (MDF), wood/polymer composite (WPC), bronzeFill, copperFill. However, there are non-plastic build materials like concrete and food as well.

A material extrusion 3D printer can have single or multiple nozzles. The number of nozzles defines how many materials can be built in the same build. The print head for thermoplastic extrusion can also have a mixer extruder to blend different thermoplastic filaments to print objects in color.

The material extrusion process is pretty much straightforward, and it is practicality undermined by few caveats like stepping, warping, or shrinkage, need for the support structure, and post-print work process. Stepping affects the finished product's smoothness. Post-print processes such as sanding and chemical treatment are required to create an entirely smooth surface. The different cool-down rates of the printed object's layer would result in warping and shrinkage. The heated build platform is used to deal with warping and shrinkage. Another preventive design is to enclose the build area and control its temperature. Besides, effective object design can help with the problem.

The overhanging or orphanage part requires a support structure in the thermoplastic extrusion process. This temporary structure needs to go through the removal process after the printout is complete. The traditional way of building a support structure is required extra effort to remove the structure using significant force, like using a knife and snapping the structure by hand, and smoothing the breakpoint by sandpaper or other means. The alternative efforts intend to make the separation more straightforward and faster. For instance, some printers use a second nozzle and water-soluble material to build a support structure.

These technological trends for the material extrusion process are discussed in [58], summarized as follows. The first trend is extrusion performance, including various build materials, color printing, multiple extrusion systems, etc. The second trend is to improve the quality of the finished product by reducing the layer thickness—print precision—and resolving the warping and shrinkage problem. The last trend is to make the post-production process easier and faster.

5.2.1. The material extrusion process feature categories

Technological trends in the material extrusion process are discussed in section 5.2. In addition to these well-tracked trends, there are other technological trends on the Kickstarter platform. Comprehensive product features extraction approach led to determining more trends, including additional capabilities such as combining milling and engraving capabilities and device interfaces. Product feature categories determined by subject matter experts based on the functionality of features are paired with technological trends in Table 12. Figure 13 illustrates how often each product feature category is highlighted in the material extrusion process projects.

Product Feature Categories	**Technological Trend**
Multiple filament Extruder	Extrusion Performance
Extruder Type and Quality	Extrusion Performance
Nozzle Size	Extrusion Performance
Filament Size	Extrusion Performance
Nozzle Type and Quality	Extrusion Performance
Non-composite Thermoplastic Filament Type	Build Material
Composite Thermoplastic Filament Type	Build Material
Food Paste Intake	Build Material
Hot End Extruder	Extrusion Performance
Visual Properties of Material	Extrusion Performance
Nozzle Cooling System	Extrusion Performance
Bowden Extruder Type	Extrusion Performance
Dissolvable Material	Post-processing
Color Printing	Extrusion Performance
Auto Z Height	Print Precision
Auto Leveling System	Print Precision
Calibration and Leveling System	Print Precision
Delta Motion System	Print Precision
Cartesian Motion System	Print Precision
Stepper Motor, Linear Bearings, Lead Screw, Belt	Print Precision
WiFi	Interface
USB Port	Interface
LCD Screen	Interface
Touch Screen	Interface
Open Source Software	Interface
Software/UI	Interface
Mobile/Web App	Interface
CNC Milling	Additional Capability
Laser Engraving	Additional Capability
Heated Bed	Warping and Shrinkage
Build Plate Materials	Warping and Shrinkage

Table 12 - Product feature categories paired with the technological trend in the material extrusion process.

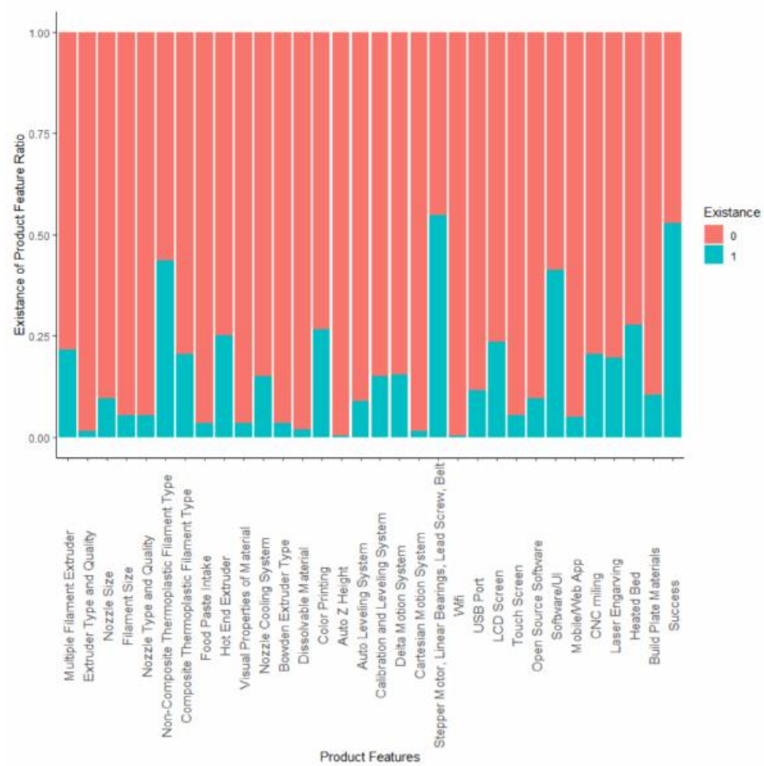

Figure 13 - Product features existence ratio for the material extrusion process.

5.2.2. The effect of features of 3D printers using material extrusion process on success of the campaign

This section provides the result of the classification model discussed in 4.4. Model considers the product feature categories—Table 12—as independent variables, and the outcome of the model is the class that projects belong to—successful or failed projects. As a result in Table 13 shows, five features are selected as significantly influential variables that explain the success or failure of the model. Selected features are mainly related to extrusion performance trends, with one exception related to building material trends.

Product Features	Dependent variable: Success (Optimal λ = 0.03691287)
Multiple Filament Extruder1	0
Extruder Type and Quality1	-1.8824761
Nozzle Size1	0
Filament Size1	0
Nozzle Type and Quality1	0.1821246
Non-Composite Thermoplastic Filament Type1	0
Composite Thermoplastic Filament Type1	0.4019609
Food Paste Intake1	0
Hot End Extruder1	0
Visual Properties of Material1	0
Nozzle Cooling System1	0.2255242
Bowden Extruder Type1	0.7679354
Dissolvable Material1	0
Color Printing1	0.6043036
Auto Z Height1	0
Auto Leveling System1	0
Calibration and Leveling System1	0
Delta Motion System1	0
Cartesian Motion System1	0
Stepper Motor, Linear Bearings, Lead Screw, Belt1	0
WiFi1	0
USB Port1	0
LCD Screen1	0
Touch Screen1	0
Open Source Software1	0
Software/UI1	0
Mobile/Web App1	0
CNC milling1	0
Laser Engraving1	0
Heated Bed1	0
Build Plate Materials1	0
Constant	-0.1674919

Table 13 - "general" classification model result considering product features as independent variables and success of the campaign as dependent variable—material extrusion process.

The classification model performance is assessed according to the confusion matrix and statistics shown in Table 14 and Table 15. The model can correctly determine the outcome of the campaign in 127 out of 199 cases. Model's accuracy is 63.82 % which is significantly better than no information—a success rate of 52.67% for the material extrusion process—with a *p*-value equal to 0.1%. Also, the model performance shows balance in both successful and failed classes considering Mcnemar's test *p*-value equal to 40.1%. The sensitivity and precision values indicate that the model performs better in failed class. However, model performs better in detecting the successful projects factoring in the prevalence of successful cases—POS vs. Neg Pred Value.

	Successful (1)	Failed (0)
Successful (1)	65	32
Failed (0)	40	62

Table 14 - Confusion matrix for the "general" model—material extrusion process.

Positive Class: 1

Accuracy	0.6382
95% CI	(0.5672, 0.705)
No Information Rate	0.5276
P-Value [ACC > NTR]	0.001053
Mcnemar's Test P-Value	0.409395
Sensitivity	0.6190
Specificity	0.6596
POS Pred Value	0.6701
Neg Pred Value	0.6078
Prevalence	0.5276
Detection Rate	0.3266
Detection Prevalence	0.4874
Balanced Accuracy	0.6393

Table 15 - Confusion statistics for the "general" model—material extrusion process.

10 folds cross-validation classification model is bootstrapped 100 times. The range of coefficients for best λ in each iteration is illustrated as a boxplot in Figure 14. The bar plot in Figure 14 shows the number of iteration in which the feature is selected as an influential factor. All the features selected have above 95% likelihood of having a non-zero coefficient. However, there are features like "Build Plate Material," "Mobile/Web App," and "Touch Screen" that show limited influence on the success of a campaign. Influential features either mask the effect of these features, or their developments are not side by side of influential features.

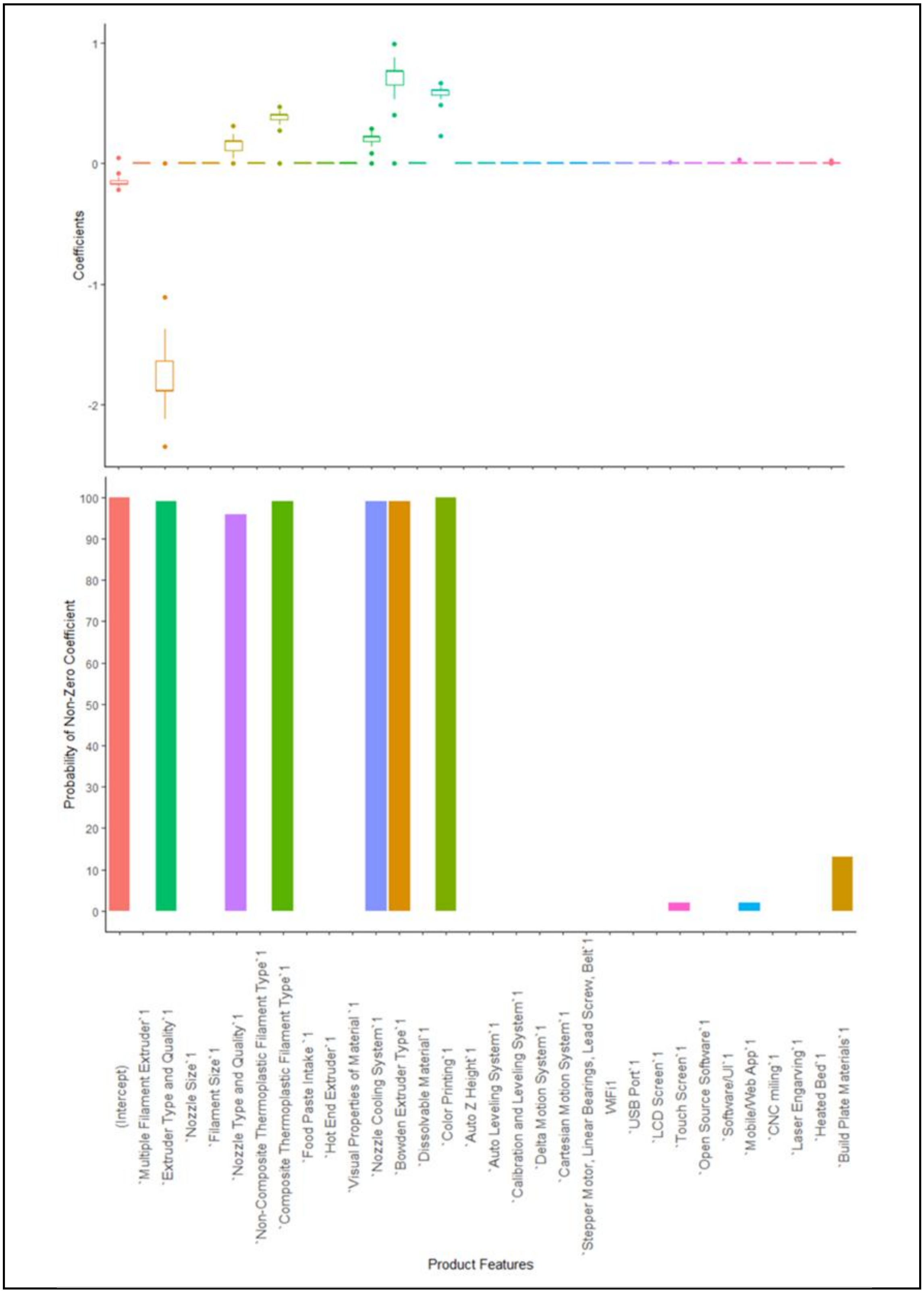

Figure 14 - Coefficient range and probability of non-zero coefficient of material extrusion process's features over 100 iterations—general model.

5.2.3. Time segmentation

One of the objectives of this study is to analyze the effect of time on the innovativeness of products in the crowdfunding environment. As shown in Figure 12, the number of launched projects from 2011-2017 follows the s-curve pattern, suggesting that the material extrusion process is reached its maturation point in 2015. The material extrusion process projects are segmented into two sections. These sections are referred to as *"early"*— projects launched before 2015—and *"recent"*— projects launched in 2015 and after—segments. This segmentation helps to capture the effect of time and product maturity on the innovativeness of the product. Another benefit of choosing 2015 for segmentation is the equal number of projects in each segment, minimizing the bias. Table 16 illustrate the classification model results in each segment. As shown, only a dominant product features trend in the "early" segment influences the success of projects.

The model has acceptable performance in the "early" segment. Confusion matrix and statistics in this segment—Table 12 and Table 13—show that the success rate is around 46%. The model's accuracy is 69.79 % which is significantly better than no information—failure rate of 54.17% in the "early" segment with a *p*-value equal to 0.1%. Also, model performance shows balance in both successful and failed classes considering Mcnemar's test *p*-value equal to 26.5%. The sensitivity and precision values indicate that the model performs better in detecting successful class. However, considering the prevalence of successful cases—POS vs. Neg Pred Value—lowers the performance of detecting the successful cases.

	Dependent variable: Success	
	Year < 2015 (Optimal λ = 0.04872644)	Year ≥ 2015 (Optimal λ = 0.107456)
Multiple Filament Extruder1	0.27199599	0
Extruder Type and Quality1	-1.46207926	0
Nozzle Size1	0	0
Filament Size1	0.83432858	0
Nozzle Type and Quality1	0	0
Non-Composite Thermoplastic Filament Type1	0	0
Composite Thermoplastic Filament Type1	0.93713899	0
Food Paste Intake1	-0.12001249	0
Hot End Extruder1	0	0
Visual Properties of Material1	-0.92903843	0
Nozzle Cooling System1	0	0
Bowden Extruder Type1	0.60984199	0
Dissolvable Material1	0	0
Color Printing1	0.65645435	0
Auto Z Height1	0	0
Auto Leveling System1	0	0
Calibration and Leveling System1	0	0
Delta Motion System1	0	0
Cartesian Motion System1	0	0
Stepper Motor, Linear Bearings, Lead Screw, Belt1	0	0
WiFi1	0	0
USB Port1	0	0
LCD Screen1	0	0
Touch Screen1	0	0
Open Source Software1	0	0
Software/UI1	0	0
Mobile/Web App1	0	0
CNC milling1	0	0
Laser Engraving1	0	0
Heated Bed1	0.08529791	0
Build Plate Materials1	0	0
Constant	-0.29779340	0.09716375

Table 16 - Classification model result considering product features as independent variables and success of the campaign as the dependent variable in the "early" and "recent" segment—material extrusion process.

	Successful (1)	Failed (0)
Successful (1)	33	18
Failed (0)	11	34

Table 17 - Confusion matrix for the "early" segment.

Positive Class: 1	
Accuracy	0.6979
95% CI	(0.5957, 0.7875)
No Information Rate	0.5417
P-Value [ACC > NTR]	0.001285
Mcnemar's Test P-Value	0.265205
Sensitivity	0.7500
Specificity	0.6538
POS Pred Value	0.6471
Neg Pred Value	0.7556
Prevalence	0.4583
Detection Rate	0.3438
Detection Prevalence	0.5312
Balanced Accuracy	0.7019

Table 18 - Confusion statistics for the "early" segment—material extrusion process.

10 folds cross-validation classification model is bootstrapped 100 times in the "early" segment. Coefficient range and probability of non-zero coefficient for best λ in each iteration are illustrated in Figure 15. All the features selected have above 80% likelihood of having a non-zero coefficient. However, only one non-selected feature, "HotEnd Extruder," shows a non-zero—around 30%— probability of influencing the campaign's success.

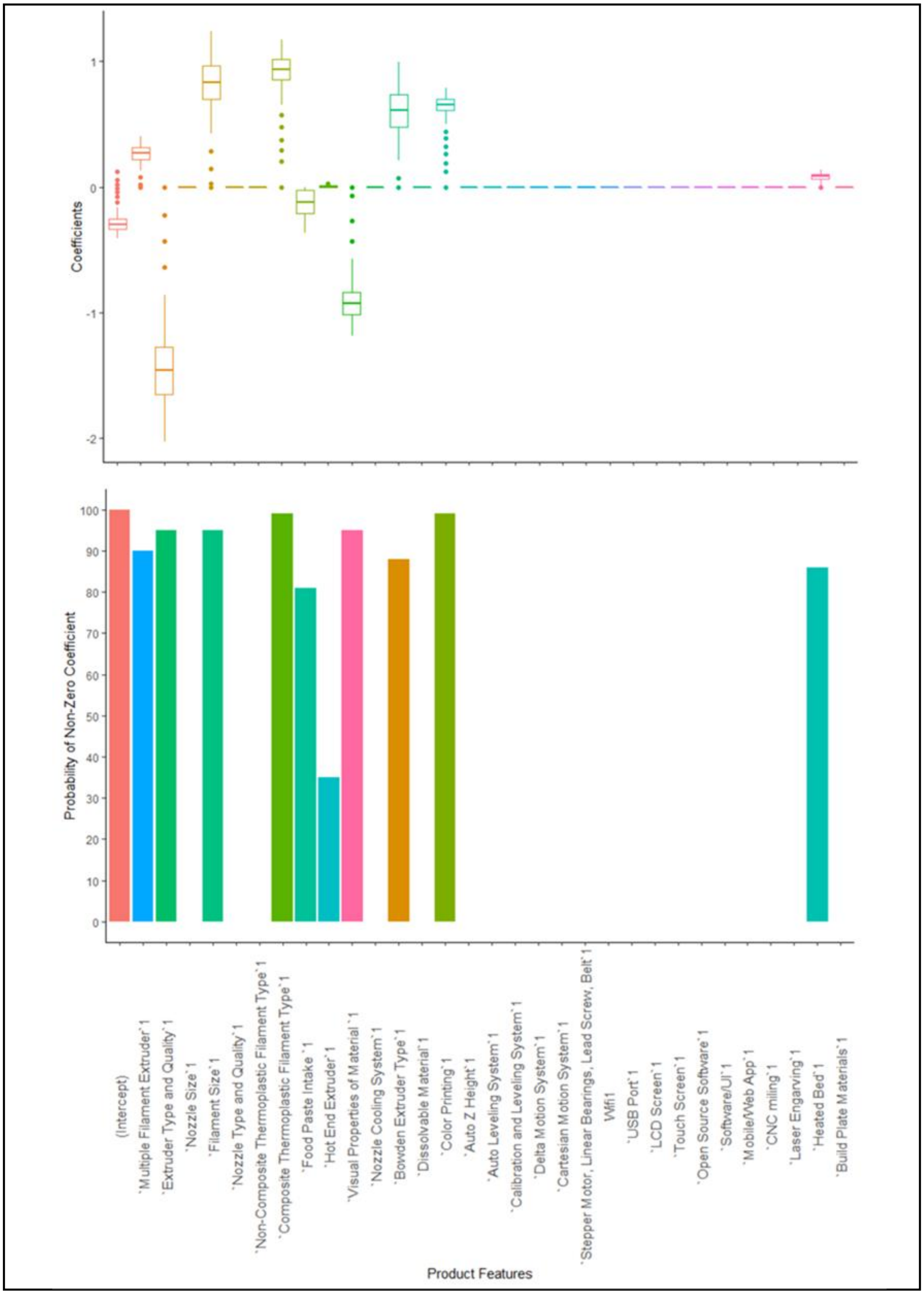

Figure 15 - Coefficient range and probability of non-zero coefficient of material extrusion process features over 100 iterations—"early" segment.

In the "recent" segment, model selects no features that influences the success of the campaign. Confusion matrix and statistics in this segment—Table 19 and Table 20—show that success rate is around 52%. The accuracy of model is not different than no information—success rate of 52.43% in "recent" segment. The other confusion statistics show the bias toward the success class, since there is no information that distinguish the failed projects.

	Successful (1)	Failed (0)
Successful (1)	54	49
Failed (0)	0	0

Table 19 - Confusion matrix for the "recent" segment.

Positive Class: 1	
Accuracy	0.5243
95% CI	(0.4235, 0.6236)
No Information Rate	0.5243
P-Value [ACC > NTR]	0.5399
Mcnemar's Test P-Value	7.025e-12
Sensitivity	1
Specificity	0
POS Pred Value	0.5243
Neg Pred Value	-
Prevalence	0.5243
Detection Rate	0.5243
Detection Prevalence	1
Balanced Accuracy	0.5

Table 20 - Confusion statistics for the "recent" segment—material extrusion process.

10 folds cross-validation classification model is bootstrapped 100 times in the "recent" segment. Coefficient range and probability of non-zero coefficient for best λ in each iteration are illustrated in Figure 16. There is no feature selected in the "recent" segment model. However, one feature, "Mobile/Web App," shows a very slim probability—below 10%—of influence on the campaign's success.

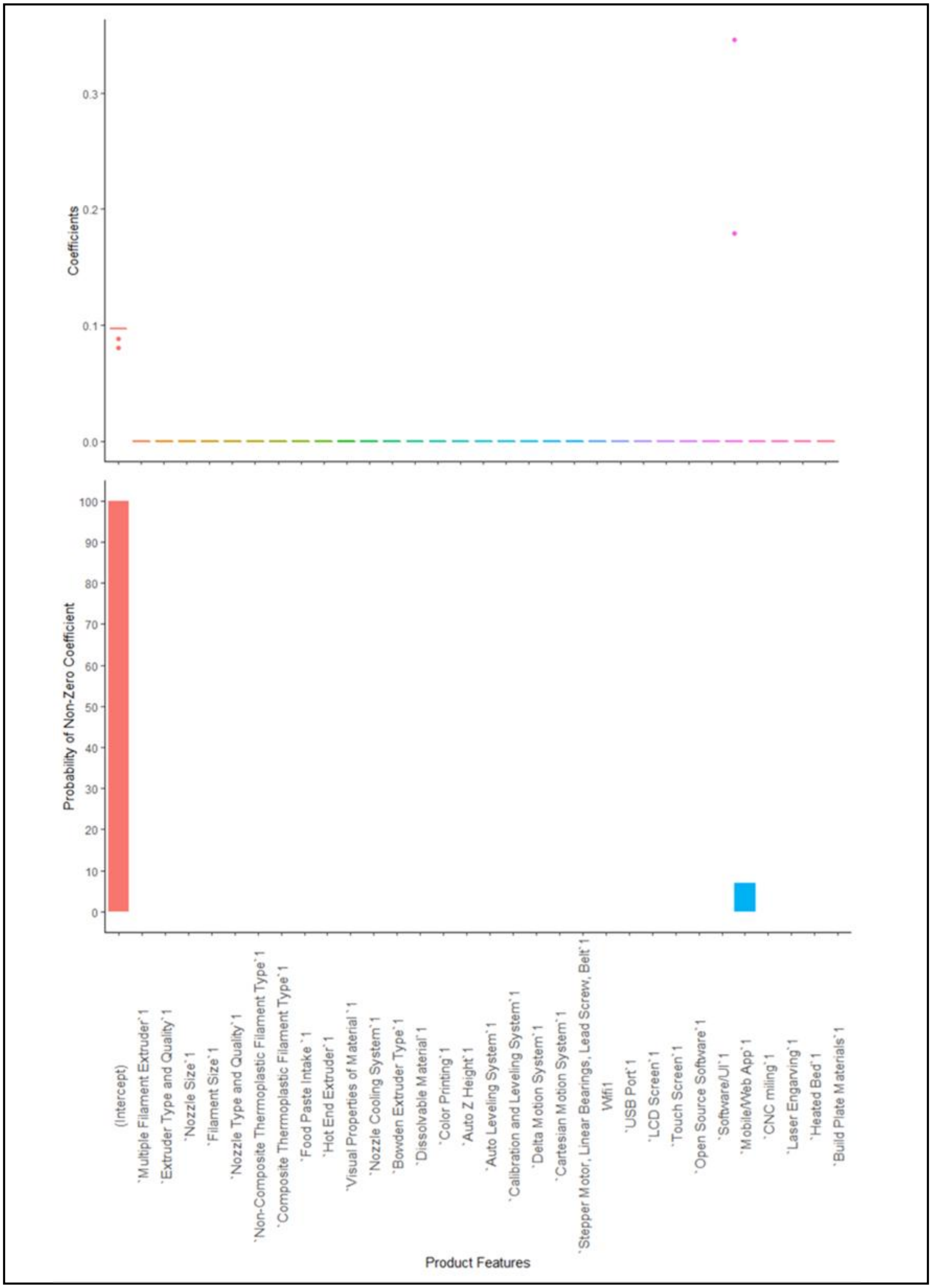

Figure 16 - Coefficient range and probability of non-zero coefficient of material extrusion process's features over 100 iterations—"recent" segment.

5.2.4. Price segmentation

The amount of pledged money is an influential factor in whether to support a project or not. Each project has various levels of reward and associated pledge money. As discussed in section 4.2.1, the average of pledged money per person is considered a product price. Figure 17 shows the price contours from 2011-2017. As shown, the price range gets wider after 2014. The price concentration is around $300-$600. However, the frequency of this price range lessens after 2014.

The price point chosen for segmentation is $400 dividing the projects into *"frugal"* and *"deep-pocket"* segments. As shown in Figure 18, $400 is a price contour that affects the success of a campaign. The projects division based on the $400 keeps the balance between the segments—regarding price median is $386 and eliminating the canceled projects with the estimated price less than $50. Furthermore, the confidence in the model results is around 90% in both "frugal" and "deep-pocket" segments at the $400 threshold—refer to Figure 19.

There is another concern with segmentation based on the estimated price of the product. As explained in section 4.2.2, excluding the appreciation rewards may increase the estimated price of the product around $400 by about $30. However, moving 12 projects with an estimated price between $350 to $400 from "frugal" to "deep-pocket" segment doesn't affect each segment's selected features. The error in estimating the price of a product has an insignificant effect on the result of the classification model.

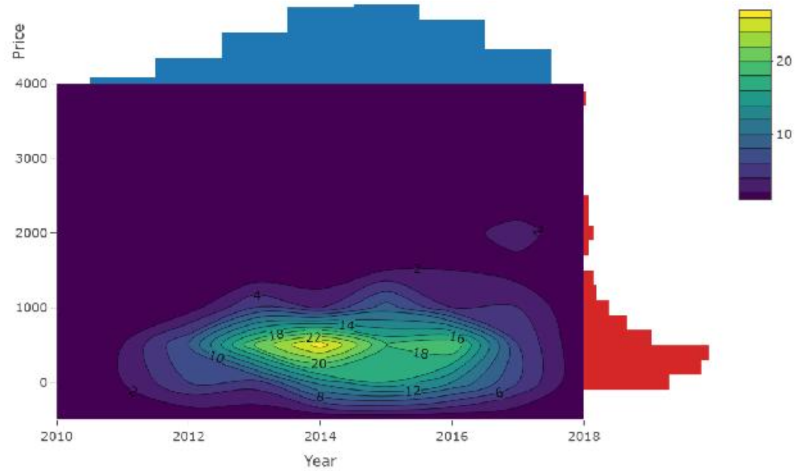

Figure 17 - Histogram 2d contour diagram of the year vs. price for material extrusion 3D printer's projects where the 3rd dimension shows the number of projects in each contour.

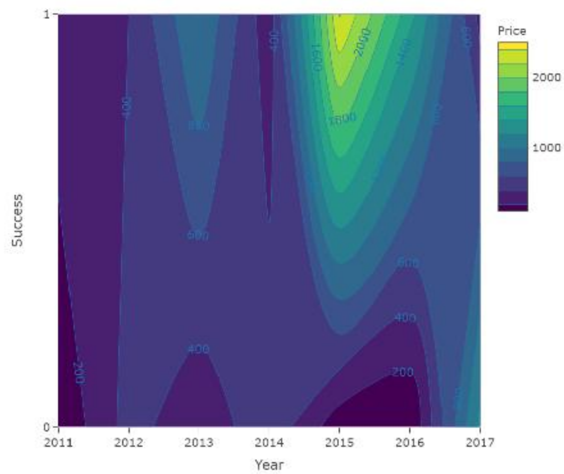

Figure 18 - 2d contour diagram of the year vs. success for material extrusion 3D printer's projects where the 3rd dimension shows the price of projects in each contour.

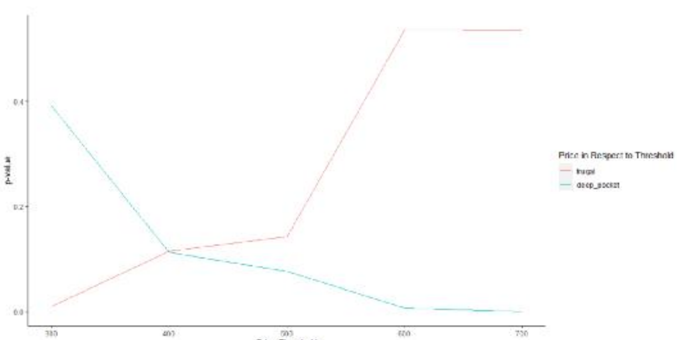

Figure 19 - Model p-value for "frugal" and "deep-pocket" segment according to different price threshold.

The results of the model in the "frugal" segment require careful considerations. Confusion matrix and statistics in this segment—Table 22 and Table 23— shows that the success rate is 47.62%. Model's accuracy is 59.52% which is significantly better than no information—failure rate of 52.38%—with a *p*-value equal to 1.1%. The rest of the confusion statistics show that only selected features in the "frugal" segment explain success in a small fraction of successful projects. Mcnemar's test *p*-value equal to 1.519e-08 indicates an imbalance in the false successful and failed outcomes. This imbalance is reflected in other statistics, including sensitivity and precision POS and Neg Pred Value. Confusion matrix and statistics indicated that "Nozzle Type and Quality" can explain the success of few projects without error. However, it is not a dominant trend in the "frugal" segment.

	Dependent variable: Success	
	50 < Price < 400 (Optimal λ = 0.09123921)	Price $\geq$ 400 (Optimal λ=0.05627943)
Multiple Filament Extruder	0	0
Extruder Type and Quality	0	-1.3591412
Nozzle Size	0	0
Filament Size	0	0
Nozzle Type and Quality	0.868360	-0.2103183
Non-Composite Thermoplastic Filament Type	0	0
Composite Thermoplastic Filament Type	0	1.0471989
Food Paste Intake	0	0
Hot End Extruder	0	0
Visual Properties of Material	0	0
Nozzle Cooling System	0	0.2162662
Bowden Extruder Type	0	0.3410441
Dissolvable Material	0	0
Color Printing	0	0.3108776
Auto Z Height	0	0
Auto Leveling System	0	0
Calibration and Leveling System	0	0
Delta Motion System	0	0
Cartesian Motion System	0	0
Stepper Motor, Linear Bearings, Lead Screw, Belt	0	0
WiFi	0	0
USB Port	0	-0.5666386
LCD Screen	0	-0.1188822
Touch Screen	0	0.1517268
Open Source Software	0	0
Software/UI	0	0
Mobile/Web App	0	0
CNC milling	0	0

Laser Engraving	0	0
Heated Bed	0	0
Build Plate Materials	0	0
Constant	-0.155502	0.5132797

Table 21 - Classification model result considering product features as independent variables and success of the campaign as the dependent variable in the "frugal" and "deep-pocket" segments—material extrusion process.

	Successful (1)	Failed (0)
Successful (1)	6	0
Failed (0)	34	44

Table 22 - Confusion matrix for the "frugal" segment.

Positive Class: 1	
Accuracy	0.5952
95% CI	(0.4825, 0.701)
No Information Rate	0.5238
P-Value [ACC > NTR]	0.1145
Mcnemar's Test P-Value	1.519e-08
Sensitivity	0.15
Specificity	1
POS Pred Value	1
Neg Pred Value	0.5641
Prevalence	0.47619
Detection Rate	0.07143
Detection Prevalence	0.07143
Balanced Accuracy	0.575

Table 23 - Confusion statistics for the "frugal" segment—material extrusion process.

Model results in the "deep-pocket" segment suffer imbalances like the "frugal" segment. However, there is a dominant design space in this segment that explains the success of the projects. Confusion matrix and statistics in this segment—Table 24 and Table 25—shows that the success rate is 67.37%. Model'accuracy is 73.62.52% which is significantly better than no information—a success rate of 67.37%—with a *p*-value equal to 1.1%. The shortcoming of this model is the lack of explanatory power of failed projects. Mcnemar's test *p*-value equal to 1.083e-05 shows an imbalance in the false successful and failed outcomes. Though the prediction value of failed projects is high regarding low prevalence, the model lacks specifying the failed projects.

	Successful (1)	Failed (0)
Successful (1)	63	24
Failed (0)	1	7

Table 24 - Confusion matrix for the "deep-pocket" segment.

Positive Class: 1	
Accuracy	0.7368
95% CI	(0.6365, 0.8219)
No Information Rate	0.6737
P-Value [ACC > NTR]	0.1131
Mcnemar's Test P-Value	1.083e-05
Sensitivity	0.9844
Specificity	0.2258
POS Pred Value	0.7241
Neg Pred Value	0.875
Prevalence	0.6737
Detection Rate	0.6632
Detection Prevalence	0.9158
Balanced Accuracy	0.6051

Table 25 - Confusion statistics for the "deep-pocket" segment—material extrusion process.

10 folds cross-validation classification model is bootstrapped 100 times in both "frugal" and "deep-pocket" segments. Figure 20 and Figure 21 show the coefficient range and probability of non-zero coefficient for best λ in each iteration for "frugal" and "deep-pocket" segments. There is no weak trend in "frugal" that is masked by selected features. However, the "Open Source Software" feature shows a slim probability—below 20%—of influence on the campaign's success, which is not selected in the "deep-pocket" model.

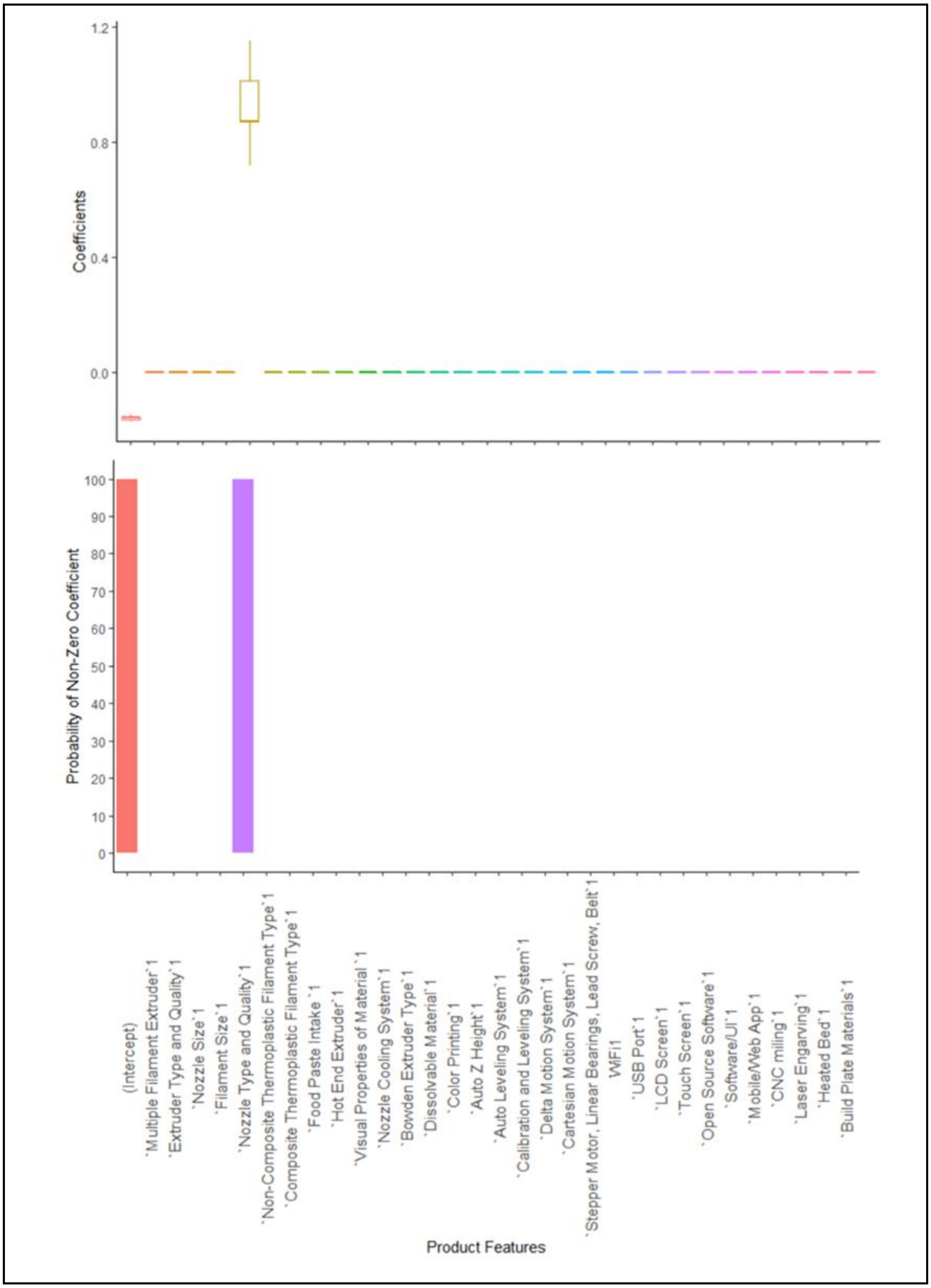

Figure 20 - Coefficient range and probability of non-zero coefficient of material extrusion process's features over 100 iterations—"frugal" segment.

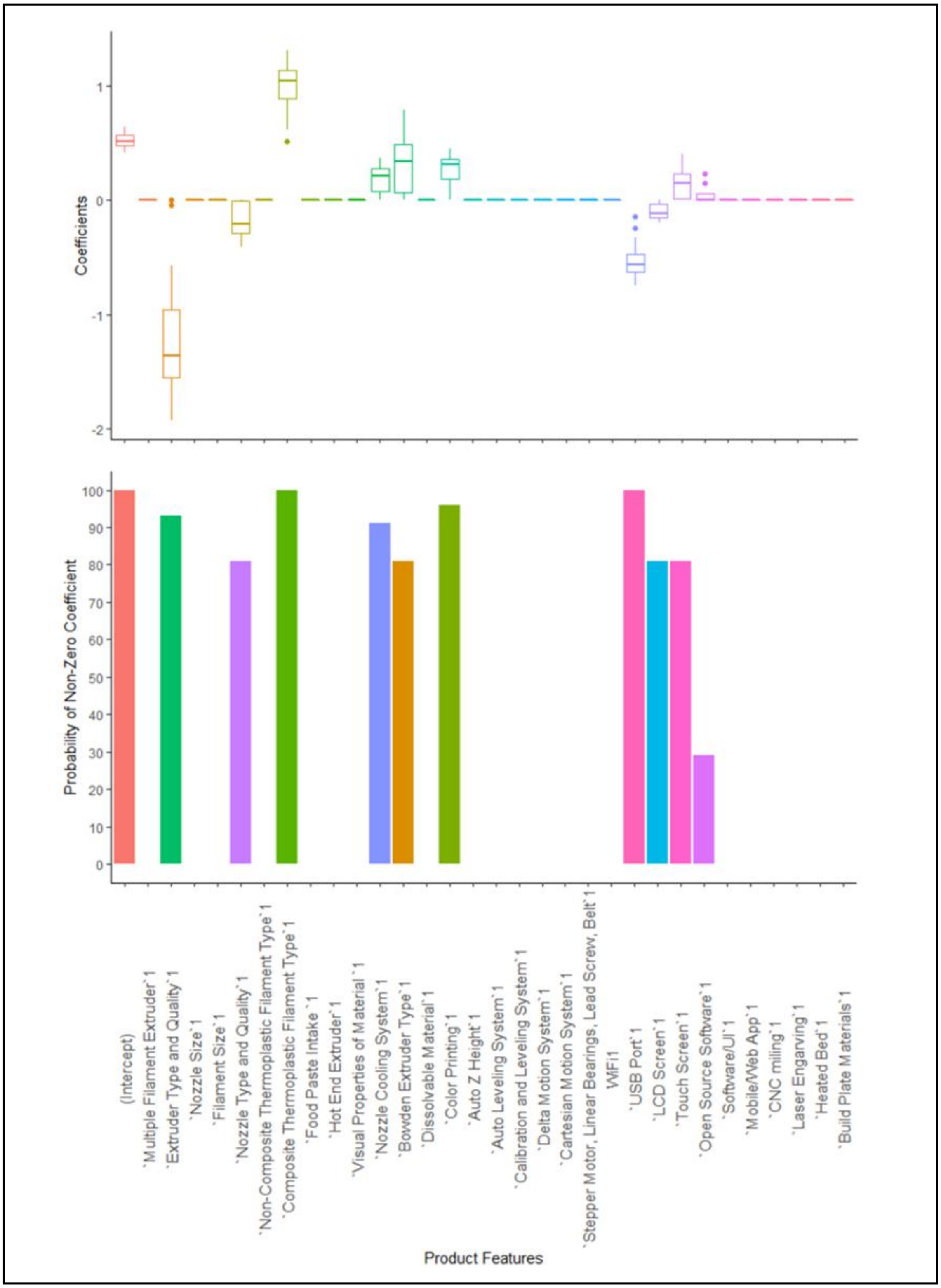

Figure 21 - Coefficient range and probability of non-zero coefficient of material extrusion process's features over 100 iterations—"deep-pocket" segment.

5.2.5. Time and price segmentation

The effect of year and price is analyzed separately so far. This section takes into consideration the effect of both factors at the same time. The same thresholds as section 5.2.35.2.4 are applied. Table 26 shows all four segments regarding time and price thresholds. As shown, these segments are labeled as *"early frugal," "early deep-pocket," "recent frugal,"* and *"recent deep-pocket."* This segmentation is intended to provide a further understanding of the relative advantages of technology products. In time segmentation, there is no technological trend in the "recent" segment.

In contrast, price segmentation suffers from an imbalance in the correct detection of successful or failed projects. There is no dominant trend that explains the majority of success in the "frugal" segment. On the other hand, the dominant trend in the "deep-pocket" segment is not doing a decent job of excluding failed projects. This section is intended to analyze the effect of factors and improve separate segmentation shortcomings.

	Year $<$ 2015	Year $\geq$ 2015
$50 <$ Price ≤ 400	"early frugal"	"recent frugal"
Price > 400	"early deep-pocket"	"recent deep-pocket"

Table 26 - Four product segments based on year and price.

	Dependent variable: Success			
	early frugal Optimal λ = 0.1453	early deep-pocket Optimal λ = 0.1105	recent frugal Optimal λ = 0.1067	recent deep-pocket Optimal λ = 0.1533
Multiple Filament Extruder1	0	0	-0.258	0
Extruder Type and Quality1	0	0	0	0
Nozzle Size1	0	0	0	0
Filament Size1	0	0	0	0
Nozzle Type and Quality1	0	0	0.6659	0
Non-Composite Thermoplastic Filament Type1	0	0	0	0
Composite Thermoplastic Filament Type1	0	0.3267	0	0
Food Paste Intake1	0	0	0	0
Hot End Extruder1	0	0	0	0
Visual Properties of Material1	0	0	0	0
Nozzle Cooling System1	0	0	0	0
Bowden Extruder Type1	0	0	0	0
Dissolvable Material1	0	0	0	0
Color Printing1	0	0.5483	0	0
Auto Z Height1	0	0	0	0
Auto Leveling System1	0	0	0	0
Calibration and Leveling System1	0	0	0	0
Delta Motion System1	0	0	0	0
Cartesian Motion System1	0	0	0	0
Stepper Motor, Linear Bearings, Lead Screw, Belt1	0	0	0	0
WiFi1	0	0	0	0
USB Port1	0	0	0	0
LCD Screen1	0	0	0	0
Touch Screen1	0	0	0	0
Open Source Software1	0	0	0	0
Software/UI1	0	0	0	0
Mobile/Web App1	0	0	0.9761	0
CNC milling1	0	0	0	0
Laser Engraving1	0	0	0	0
Heated Bed1	0	0	0	0
Build Plate Materials1	0	0	0	0
Constant1	-0.0953	0.5208	-0.1967	0.6633

Table 27 - Classification model result considering product features as independent variables and success of the campaign as the dependent variable in "early frugal," "early deep-pocket," "recent frugal," "recent deep-pocket" segments—material extrusion process.

Table 27 shows the result of the classification model in four segments. The selected features in the "early frugal" and "recent deep-pocket" segments don't provide additional insight. In contrast, the model result in the "early deep-pocket" and "recent frugal" segments further insights gained in time segmentation and price segmentation. The selected features in "recent frugal" segments improve the lack of insight in the "recent" segment. Also, dividing the "deep-pocket" into "early" and "recent" adds more insight into technological trends that impact the success of a campaign. Regardless of additional insights into technological trends, considering the effect of time and price doesn't eliminate the imbalance in the false success or failed outcomes—refer to Table 30, Table 31, Table 32, and Table 33.

	Successful (1)	Failed (0)
Successful (1)	0	0
Failed (0)	20	22

Table 28 - Confusion matrix for "early frugal" segment.

Positive Class: 1	
Accuracy	0.5238
95% CI	(0.3642, 0.68)
No Information Rate	0.5238
P-Value [ACC > NTR]	0.5622
Mcnemar's Test P-Value	2.152e-05
Sensitivity	0
Specificity	1
POS Pred Value	-
Neg Pred Value	0.5238
Prevalence	0.4762
Detection Rate	0
Detection Prevalence	0
Balanced Accuracy	0.5

Table 29 - Confusion statistics for "early frugal" segment—material extrusion process.

	Successful (1)	Failed (0)
Successful (1)	31	14
Failed (0)	0	0

Table 30 - Confusion matrix for "early deep-pocket" segment.

Positive Class: 1	
Accuracy	0.6889
95% CI	(0.5335, 0.8183)
No Information Rate	0.6889
P-Value [ACC > NTR]	0.571667
Mcnemar's Test P-Value	0.000512
Sensitivity	1
Specificity	0
POS Pred Value	0.6889
Neg Pred Value	-
Prevalence	0.6889
Detection Rate	0.6889
Detection Prevalence	1
Balanced Accuracy	0.5

Table 31 - Confusion statistics for "early deep-pocket" segment—material extrusion process.

	Successful (1)	Failed (0)
Successful (1)	7	0
Failed (0)	13	22

Table 32 - Confusion matrix for "recent frugal" segment.

Positive Class: 1	
Accuracy	0.6905
95% CI	(0.5291, 0.8238)
No Information Rate	0.5238
P-Value [ACC > NTR]	0.021248
Mcnemar's Test P-Value	0.0008741
Sensitivity	0.35
Specificity	1
POS Pred Value	1
Neg Pred Value	0.6286
Prevalence	0.4762
Detection Rate	0.1667
Detection Prevalence	0.1667
Balanced Accuracy	0.675

Table 33 - Confusion statistics for "recent frugal" segment—material extrusion process.

	Successful (1)	Failed (0)
Successful (1)	33	17
Failed (0)	0	0

Table 34 - Confusion matrix for "recent deep-pocket" segment.

Positive Class: 1

Accuracy	0.66
95% CI	(0.5123, 0.7879)
No Information Rate	0.66
P-Value [ACC > NTR]	0.5654133
Mcnemar's Test P-Value	0.0001042
Sensitivity	1
Specificity	0
POS Pred Value	0.66
Neg Pred Value	-
Prevalence	0.66
Detection Rate	0.66
Detection Prevalence	1
Balanced Accuracy	0.5

Table 35 - Confusion statistics for "recent deep-pocket" segment—material extrusion process.

Segmentation exacerbates the curse of dimensionality problem. It also lessens the chance of finding the dominant trends that explain the success or failure of a campaign. Although further segmentation considering time and price together doesn't result in finding dominant trends that explain the success and failure of the campaign equally, it helps identify weaker trends. As shown in Figure 22, Figure 23, Figure 24, and Figure 25, a wide range of features shows various impact levels. These weak trends are utilized in section 5.2.6 to draw insight into the relative advantage of technology products. The findings related to these weak trends are verified by subject matter expert.

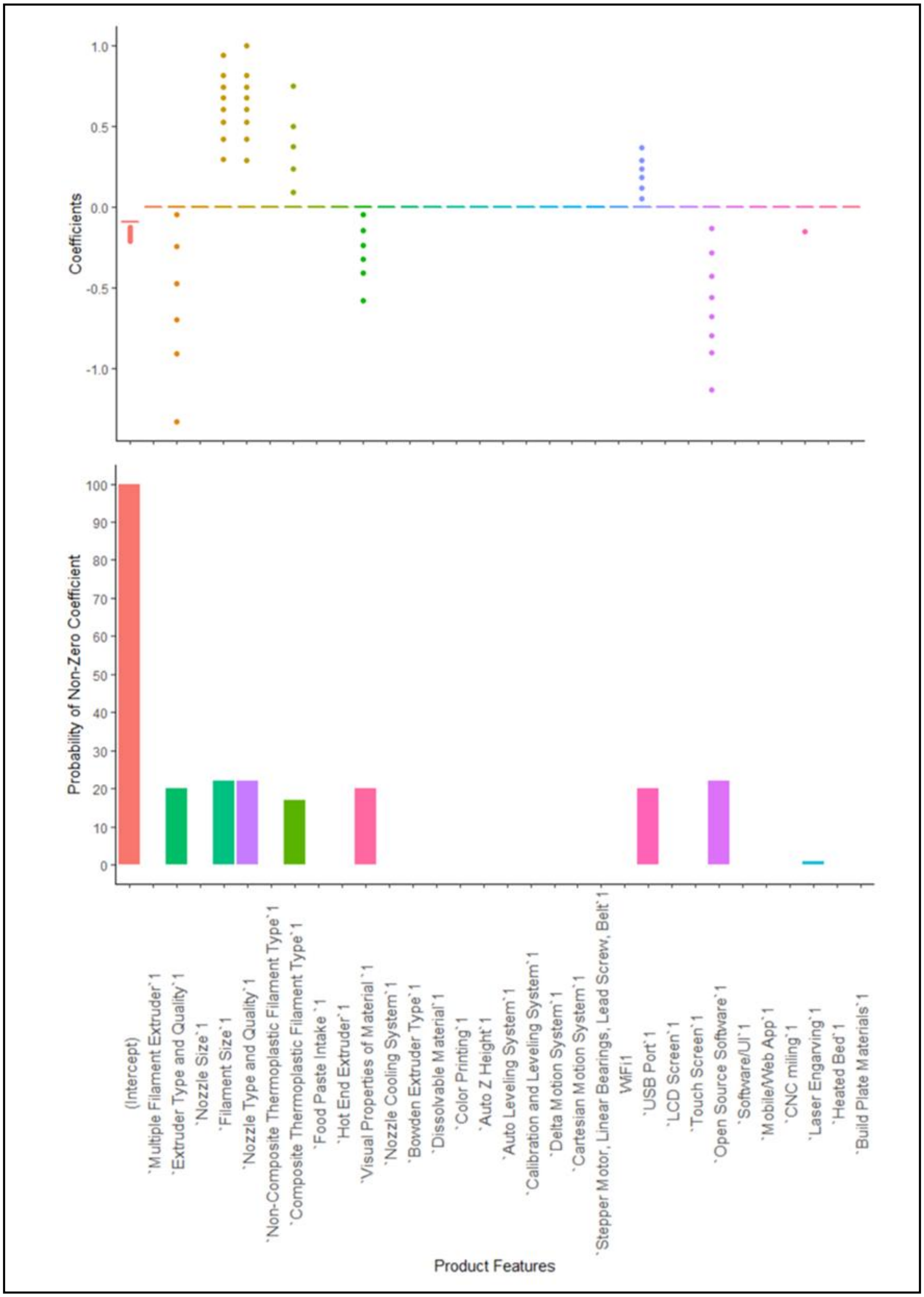

Figure 22 - Coefficient range and probability of non-zero coefficient of material extrusion process's features over 100 iterations—"early frugal" segment.

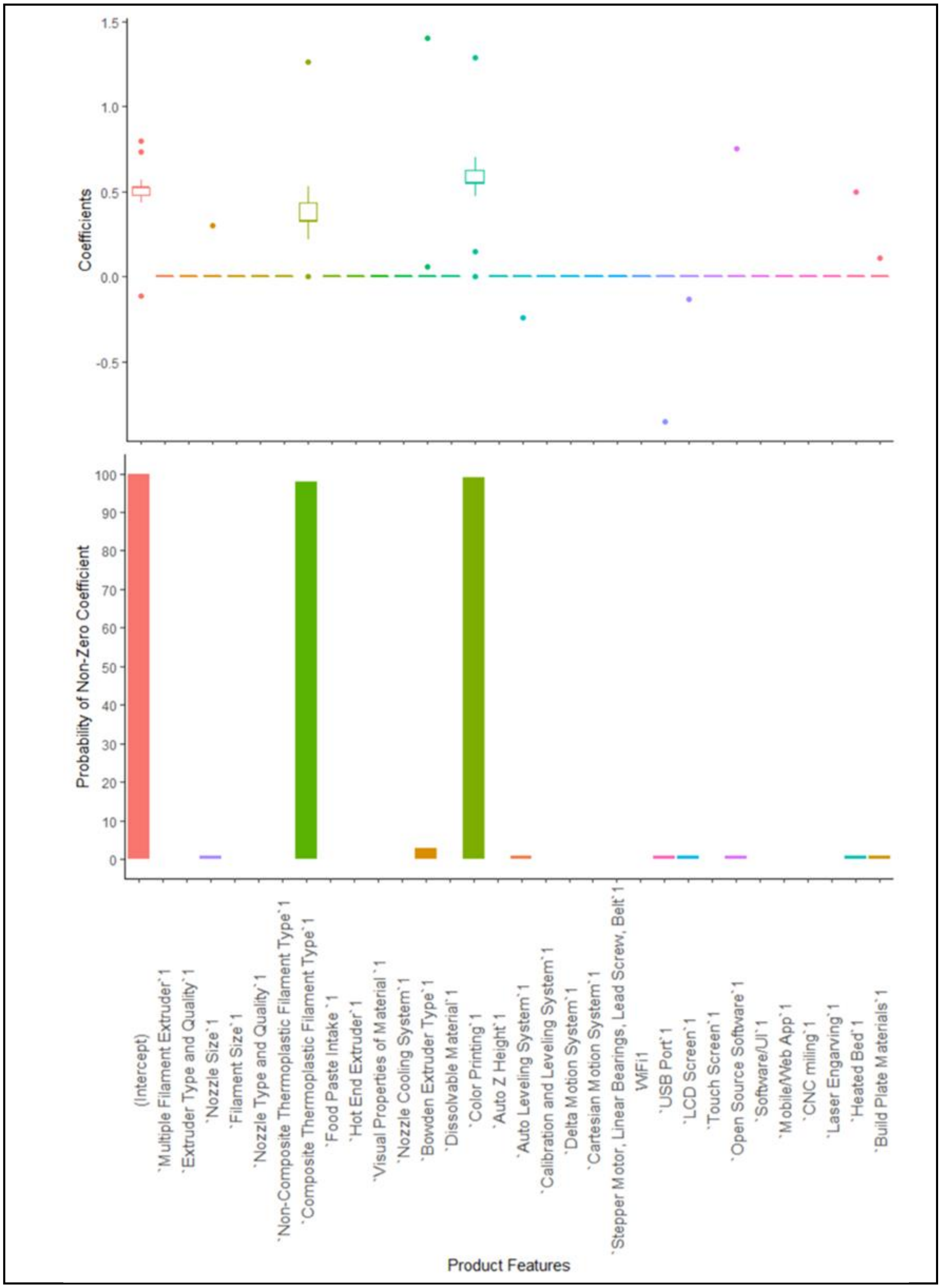

Figure 23 - Coefficient range and probability of non-zero coefficient of material extrusion process's features over 100 iterations—"early deep-pocket" segment.

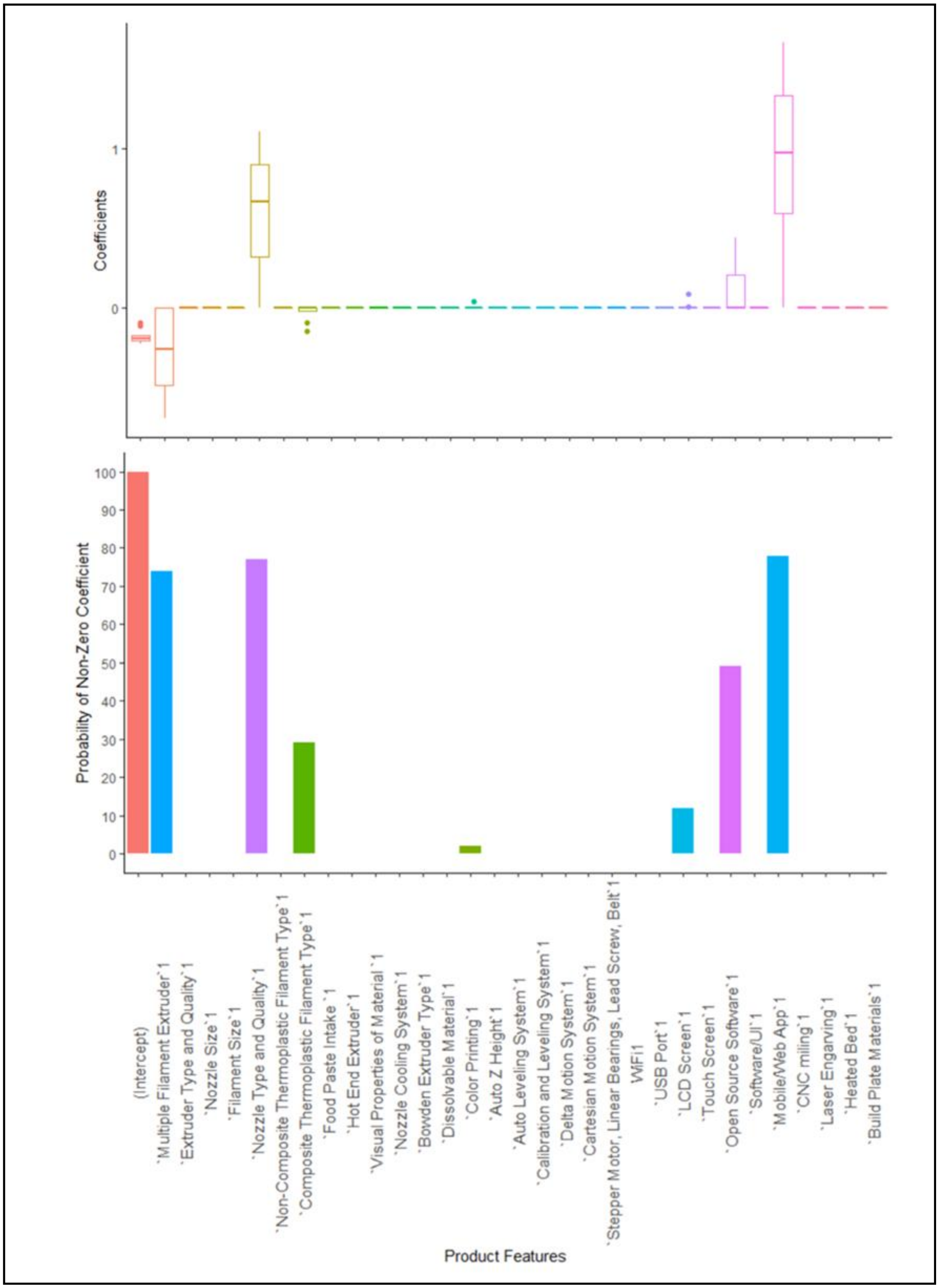

Figure 24 - Coefficient range and probability of non-zero coefficient of material extrusion process's features over 100 iterations—"recent frugal" segment.

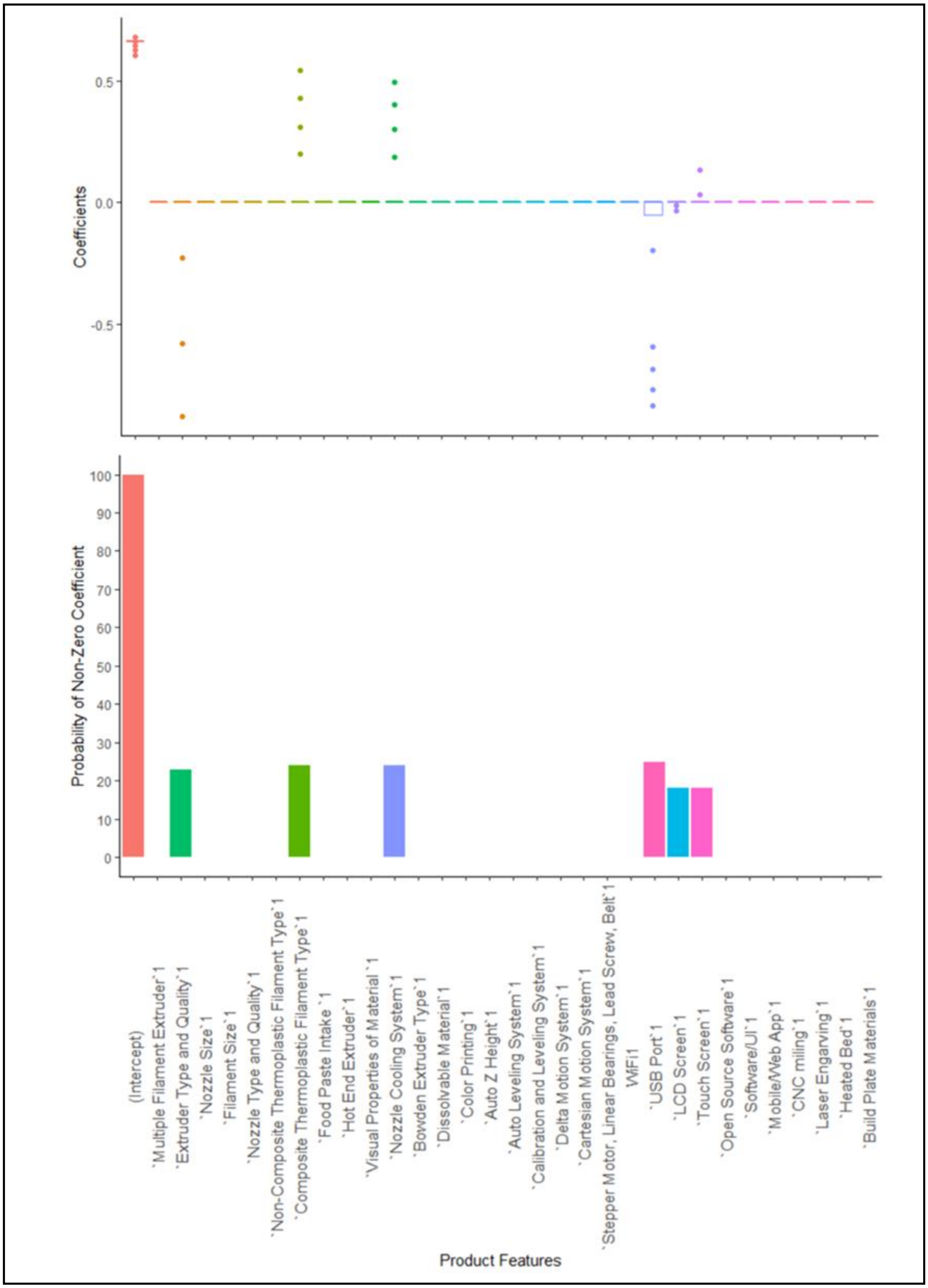

Figure 25 - Coefficient range and probability of non-zero coefficient of material extrusion process's features over 100 iterations—"recent deep-pocket" segment.

5.2.6. The material extrusion process results overview

This section is intended to analyze the material extrusion process results. The analysis aims to draw meaningful and plausible insights from the classification model results into how product features influence the campaign's success. Three consequential components are considered to derive the factors that influence the perceived value of 3D printers that use the material extrusion process. The first component compares the impact of product features in the "general model"—sections 5.2.2—and in various segmentations—section 5.2.3, 5.2.4, and 5.2.5. The second component is the effect of handling sparsity and statistical validation on the product features' impact. The third component construes the perceived value of features regarding the first and second components.

As discussed in Product feature scarcity vs. dimensionality reduction as part of Analytic generalization and transferability, one of the difficulties of this work is balancing the statistical validation and confidence in findings. Feature selection process, which deals with the dimensionality issue, can overlook the impact of less influential features. It is vital to break down the selection process and connect the process with the feature demand. The effect of the feature selection and model validation process can be evaluated by answering the following three questions:

a) What are the metrics determining the feature influence in the success of the campaign? What is the interaction pattern between these metrics?

Feature selection addresses the curse of dimensionality, including overfitting and closeness of data. Three main factors influence the selection of features—feature frequency, discriminative power of feature to distinguish classes, and co-occurrence with influential features. The material extrusion process features frequency and discriminative power is shown in Table 36 and Figure 26 illustrates the co-occurrence map of these features. The frequency of features means how many projects mentioned the feature on their page. The ratio of the probability of a feature's existence in a successful campaign to the probability of the existence of a feature in a failed campaign represents the discriminative power of the feature or strength of association with one of the classes. The co-occurrence map shows how many time features appeared together.

Selected features in the "general" model—Table 13—are highlighted in Table 36 and Figure 26. The dominant pattern is that all the selected features show high association with one class—successful or failed campaign. For influential features, the ratio of the probability of a feature's existence in a successful campaign to the probability of the existence of a feature in a failed campaign is either significantly close to 0 or higher than 1. Besides, the less frequent features require a stronger association to be selected. For instance, "Nozzle Cooling System" and "Build Plate Materials" have similar association strength and co-occur with other selected features. Unlike "Nozzle Cooling System" that is part of the final selected features, "Build Plate Materials" chosen only in a few data subsets, as shown in Figure 14. As shown in Table 36, the "Nozzle Cooling System" is on the threshold of association strength and frequency combination. Thus, "Build Plate Materials" with lower frequency is required a stronger association to make the cut.

Co-occurrence is also an essential factor. Another pattern is that all the selected features are co-occurred at least one time. For instance, "Nozzle Type and Quality" and "Touch Screen" have similar metrics. However, they have slightly different co-occurrence patterns, making the model choose the former features, not the latter. "Nozzle Type and Quality" co-occur with all other selected features, whereas "Touch Screen" co-occur with all other chosen features except one. The co-occurrence of features is directly related to the closeness of data issue, so removing "Nozzle Type and Quality" with a slightly better pattern won't shift power to "Touch Screen." The only scenario that forces the classification model to select "Touch Screen" is finding a subset of data in which "Touch Screen" co-occur with all other selected features. As shown in Figure 14, in a few subsets of data where the "Touch Screen" co-occurs have a non-zero coefficient that indicates it co-occurred with all of the selected features in those subsets.

Product Features	Freq	Overall Ratio of Existence	Probability of Existence in Successful Campaign	Probability of Existence in Failed Campaign	Ratio of the probability of Existence in Successful to Failed Campaign
Stepper Motor, Linear Bearings, Lead Screw, Belt	109	0.55	0.55	0.54	1.018
Non-Composite Thermoplastic Filament Type	87	0.44	0.49	0.38	1.27
Software/UI	82	0.41	0.45	0.37	1.2
Heated Bed	55	0.28	0.28	0.28	1
Color Printing	53	0.27	0.35	0.17	2.07
Hot End Extruder	50	0.25	0.28	0.22	1.23
LCD Screen	47	0.24	0.22	0.26	0.86
Multiple Filament Extruder	43	0.22	0.25	0.18	1.37
Composite Thermoplastic Filament Type	41	0.21	0.27	0.14	1.93
CNC milling	41	0.21	0.22	0.19	1.44
Laser Engraving	39	0.2	0.21	0.18	1.16
Delta Motion System	31	0.16	0.15	0.16	0.95
Nozzle Cooling System	30	0.15	0.19	0.11	1.79
Calibration and Leveling System	30	0.15	0.14	0.16	0.9
USB Port	23	0.12	0.1	0.13	0.8
Build Plate Materials	21	0.11	0.13	0.07	1.8
Nozzle Size	19	0.1	0.1	0.09	1.23
Open Source Software	19	0.1	0.1	0.09	1.23
Auto Leveling System	18	0.09	0.1	0.07	1.41
Filament Size	11	0.06	0.07	0.04	1.57
Nozzle Type and Quality	11	0.06	0.08	0.03	2.39
Touch Screen	11	0.06	0.08	0.03	2.39
Mobile/Web App	10	0.05	0.07	0.04	2.08
Food Paste Intake	7	0.04	0.03	0.04	0.67
Visual Properties of Material	7	0.04	0.04	0.03	1.19
Bowden Extruder Type	7	0.04	0.06	0.01	5.37
Dissolvable Material	4	0.02	0.03	0.01	2.69
Extruder Type and Quality	3	0.02	0	0.03	0
Cartesian Motion System	3	0.02	0.02	0.01	1.79
Auto Z Height	1	0.005	0.01	0	Inf.
WiFi	1	0.005	0.01	0	Inf.

Table 36 - Metrics of features of the material extrusion process.

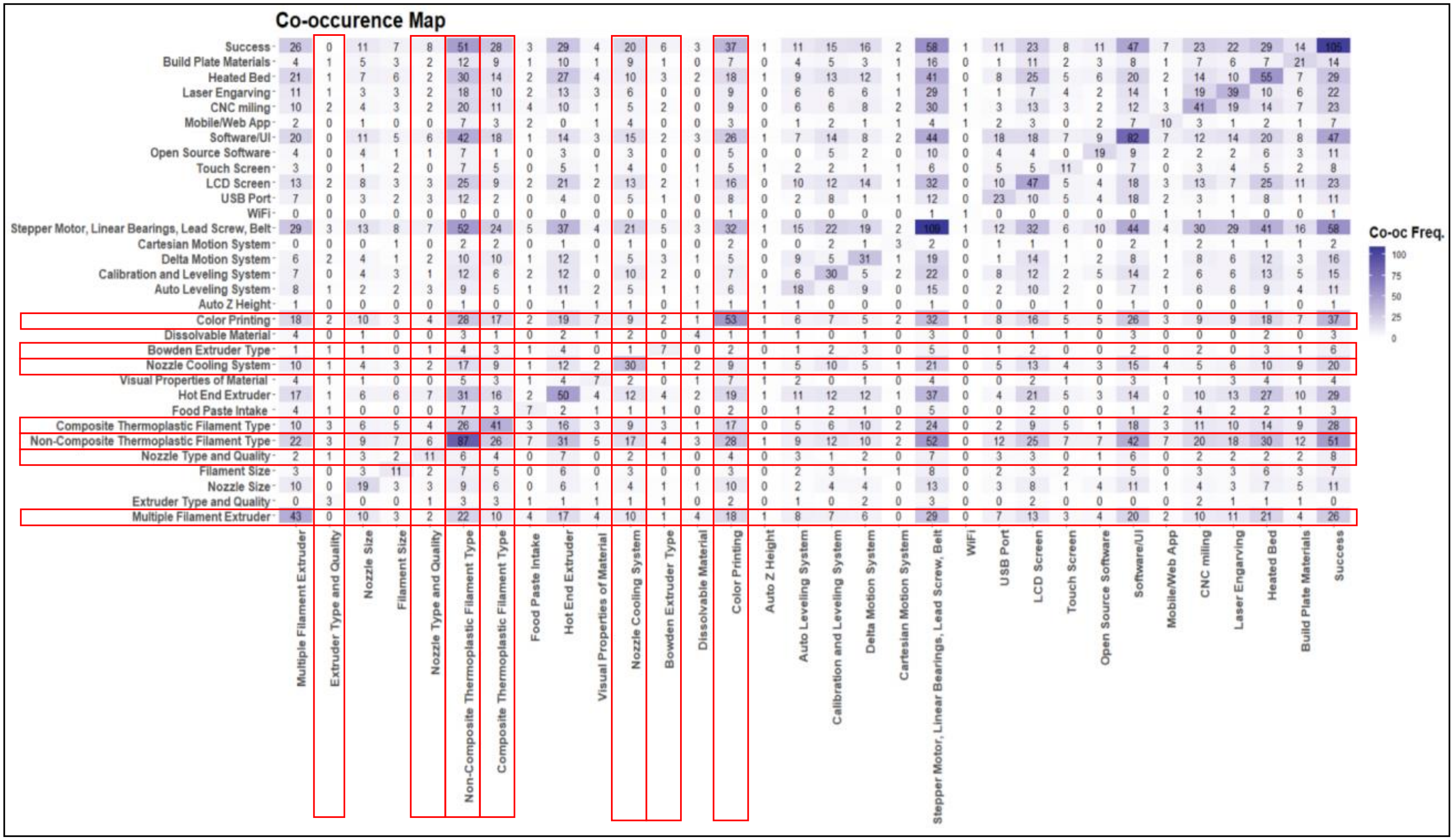

Figure 26 - Co-occurrence map of features of the material extrusion process.

b) What is the meaning of these metrics in terms of feature demand?

This question explores the meaning of discussed metrics above in terms of feature demand regarding the diffusion of innovation theory. The product features are categorized based on frequency and strength of association in Table 37. Frequency shows how widespread the features are. In contrast, the high association of features with the campaign's outcome indicates the feature's distinctiveness. However, low association means that the feature is either a fundamental part of the product or demand for the feature is saturated. Highlighting an integral part is necessary to assure the product's functionality and the distinctive feature to emphasize the product's innovativeness. Table 37 shows all four categories regarding frequency and association level. Features with a high association are distinctive features that are widespread or new according to the frequency. Features with the low association are either fundamental features or matured distinctive features that are widespread or limited.

		Association	
		High	**Low**
Frequency	**High**	Widespread distinctive features	Widespread integral or matured distinctive features
	Low	New distinctive features	matured limited features or rarely mentioned fundamental feature

Table 37 - Interaction of frequency and association of feature regarding feature type and demand.

The co-occurrence of features conveys the integrated design space. The lasso model finds the main design space that defines the overall technology trends over time. If the feature does not belong to the dominant design space, it won't get selected. The unconnected distinctive feature—"branched design" space—can influence the outcome of a campaign. However, their influence can't be statistically validated. A feature that has a comparable degree of association and similar co-occurrence with selected features won't get selected if it has a lower frequency. So, the effect of a feature can get masked with a feature that has a stronger influence. This study tries to gain more insight beyond the dominant technology trend by time and price segmentation and visualizing the range and the probability of non-zero coefficients.

Technological Development Trends	**Frequency**	**Association**	**Co-occurrence**	**Selected**	**Example**
"Main Design" Space (MDS)	High/Low	High	All features in MDS	Yes	"Nozzle Cooling System" "Nozzle Type and Quality"
Weak Trends in MDS	Lower than MDS feature with similar association and co-occurrence	High	All features in MDS	No	"Build Plate Material"
"Branched Design" Space (BDS)	High/Low	High	Some of the features in MDS	No	"Touch Screen"

Table 38 - Technological Development Trends categorization based on the metrics and classification model results.

c) How time and price segmentation influence these metrics?

Time and price segmentations have several effects that help with providing more insight about product features' impact on the success of a campaign. Segmentation affects all three metrics—frequency, association, and co-occurrence. Like the "general" model, features require high association with the campaigns' outcome to be selected or have a non-zero likelihood of non-zero coefficient. However, segmentation can strengthen, weaken association or change the inclination toward another class. "Nozzle Type and Quality" is a good example of the effect of segmentation on association. This feature positively impacts the success of a campaign in the "general" model and "frugal"—especially "recent frugal." However, the impact is reversed in the "deep-pocket" segment.

The difference in the direction of impact has resulted from changes of association from one class to another.

In contrast, it is expected that segmentation generally lowers the frequency of features in each segment. Consequently, a decline in frequency lowers the chance of co-occurrence in feature. As the chance of co-occurrence of features lessens, the co-occurrence importance plays a less significant role in the selected features providing an opportunity to "branched design" space to show impact. For instance, "Mobile/Web App" isn't among selected features in the "general" model, although it shows a non-zero probability of having non-zero coefficients in the "general" model—Figure 14. Based on categorization in Table 38, "Mobile/Web App" is a "branched design" space. So, segmentation provides an opportunity to detect branched developments.

Less frequency and co-occurrence also weakens the dominant design space trends and provides an opportunity for a weaker trend to get detected. However, the interaction between frequency and co-occurrence affects the performance of the classification model. If the co-occurrence doesn't decline enough, there is inconclusiveness about which features have a dominant effect on the outcome. The absence of dominant design space leads to no selection with features showing the same probability of having non-zero coefficients. This effect is observed in the "early frugal" segment result—Figure 22. For example, "Nozzle Type and Quality" has a higher probability and has been selected in the "recent frugal" segment.

In contrast, in the "early frugal" segment, "Nozzle Type and Quality" has a lower probability compared to the "early frugal" segment. However, the frequency and association of the features are similar in both segments—Table 40. "Nozzle Type and Quality" co-occur with four features with a non-zero likelihood of having a non-zero coefficient in the "early frugal" segment. In comparison, it has only one co-occurrence in the "recent frugal" segment—Figure 27 and Figure 29.

Segmentation and breaking dominant design space have another adverse effect on classification model performance. In the absence of a dominant design space that explains the outcome of campaigns, the classification model experiences imbalance in the goodness of performance in one class over another. Table 39 shows an imbalance in model performance in four segments. The imbalance is related to the dominance of one outcome over another and the power of selected features to explain the infrequent outcome. For instance, failed campaign is a dominant outcome in the "recent frugal" segment. However, the selected feature only has the power to distinguish seven successful projects.

		Early		Recent	
		Success	Failure	Success	Failure
Frugal	Predicted Success	0	0	7	0
	Predicted Failure	20	22	13	22
Deep-pocket	Predicted Success	31	14	33	17
	Predicted Failure	0	0	0	0

Table 39 - Confusion matrix of classification model for four segments according to year and price.

Segment	Product Features	Freq.	Probability of Existence in Successful Campaign	Probability of Existence in Failed Campaign	Ratio of the probability of Existence in Successful to Failed Campaign
Early Frugal	Composite Thermoplastic Filament Type	8	0.25	0.1	2.58
	USB Port	6	0.2	0.06	3.1
	Laser Engraving	6	0.05	0.16	0.31
	Open Source Software	4	0	0.13	0
	Filament Size	3	0.15	0	Inf.
	Nozzle Type and Quality	3	0.15	0	Inf.
	Extruder Type and Quality	2	0	0.06	0
	Visual Properties of Material	2	0	0.06	0
Early Deep-Pocket	Color Printing	19	0.55	0.14	3.84
	Heated Bed	19	0.48	0.29	1.7
	LCD Screen	15	0.29	0.43	0.68
	Composite Thermoplastic Filament Type	9	0.29	0	Inf.
	Open Source Software	9	0.23	0.14	1.58
	USB Port	8	0.13	0.29	0.45
	Nozzle Size	6	0.16	0.07	2.26
	Build Plate Materials	6	0.16	0.07	2.26
	Auto Leveling System	4	0.06	0.14	0.45
	Bowden Extruder Type	4	0.13	0	0.45
Recent Frugal	LCD Screen	11	0.24	0.19	1.27
	Color Printing	9	0.24	0.13	1.9
	Multiple Filament Extruder	7	0.05	0.19	0.25
	Mobile/Web App	4	0.19	0	Inf.
	Open Source Software	3	0.1	0.03	3.05
	Nozzle Type and Quality	3	0.14	0	Inf.
Recent Deep-Pocket	Composite Thermoplastic Filament Type	11	0.3	0.06	5.15
	LCD Screen	11	0.16	0.35	0.43
	Nozzle Cooling System	6	0.19	0	Inf.
	USB Port	5	0.03	0.24	0.13
	Touch Screen	4	0.12	0	Inf.
	Extruder Type and Quality	1	0	0.06	0

Table 40 - Metrics of features with a non-zero likelihood of non-zero coefficients in four segments—the material extrusion process.

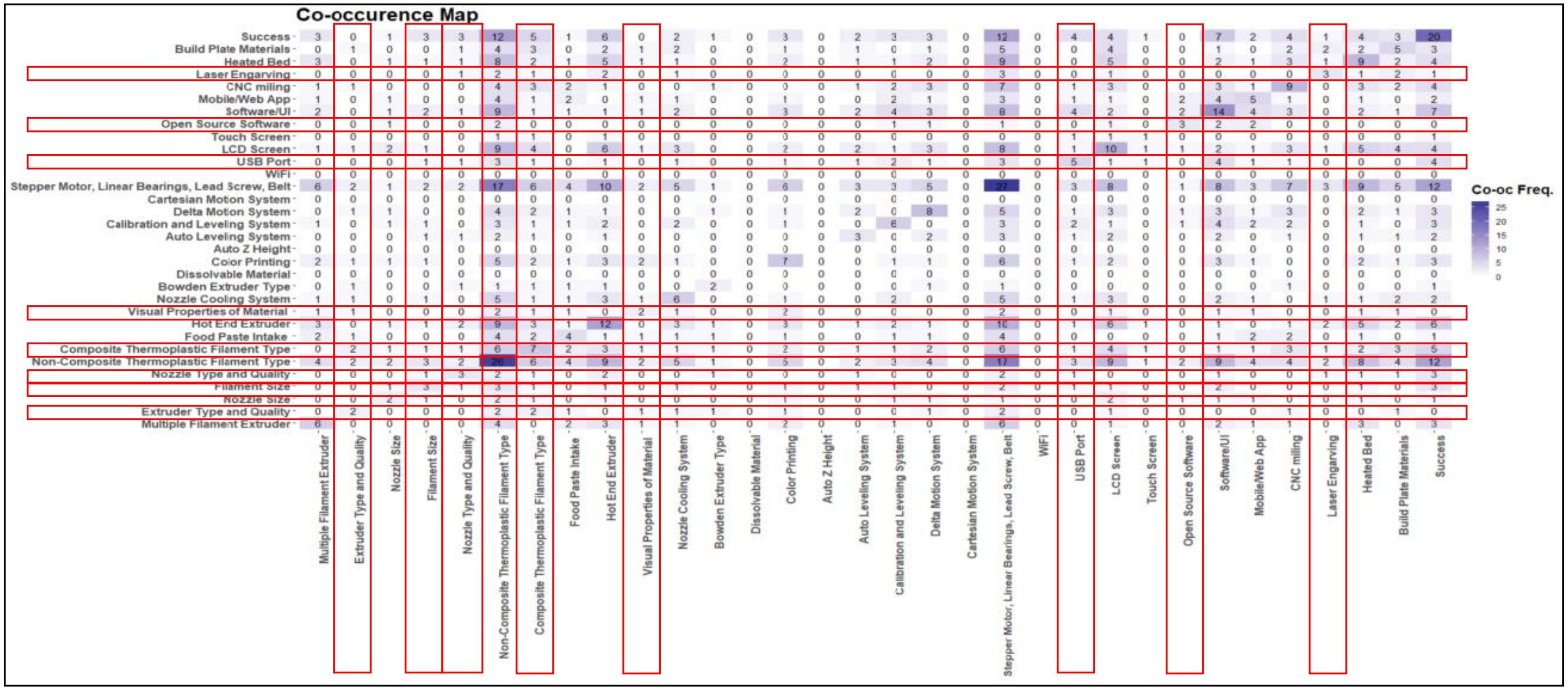

Figure 27 - Co-occurrence map of features of the material extrusion process for the "early frugal" segment.

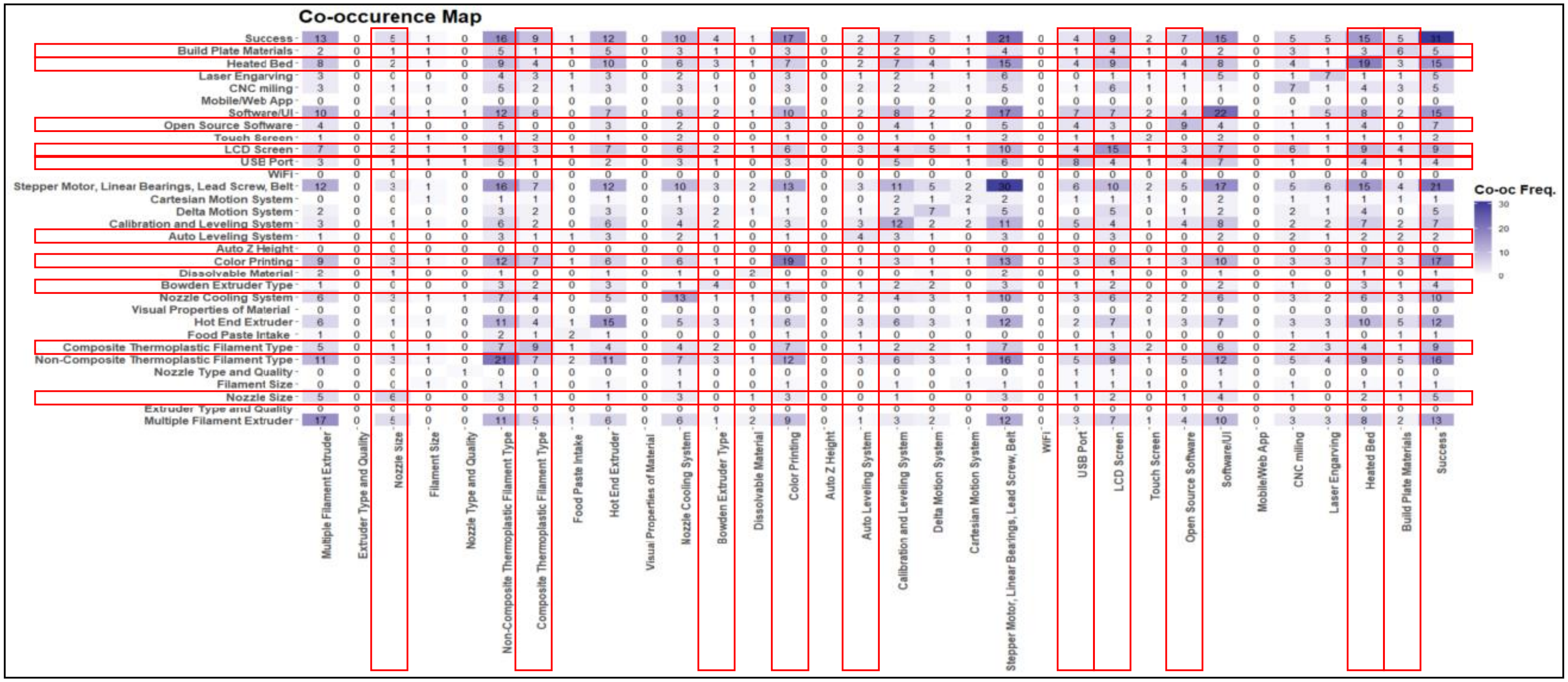

Figure 28 - Co-occurrence map of features of the material extrusion process for the "early deep-pocket" segment.

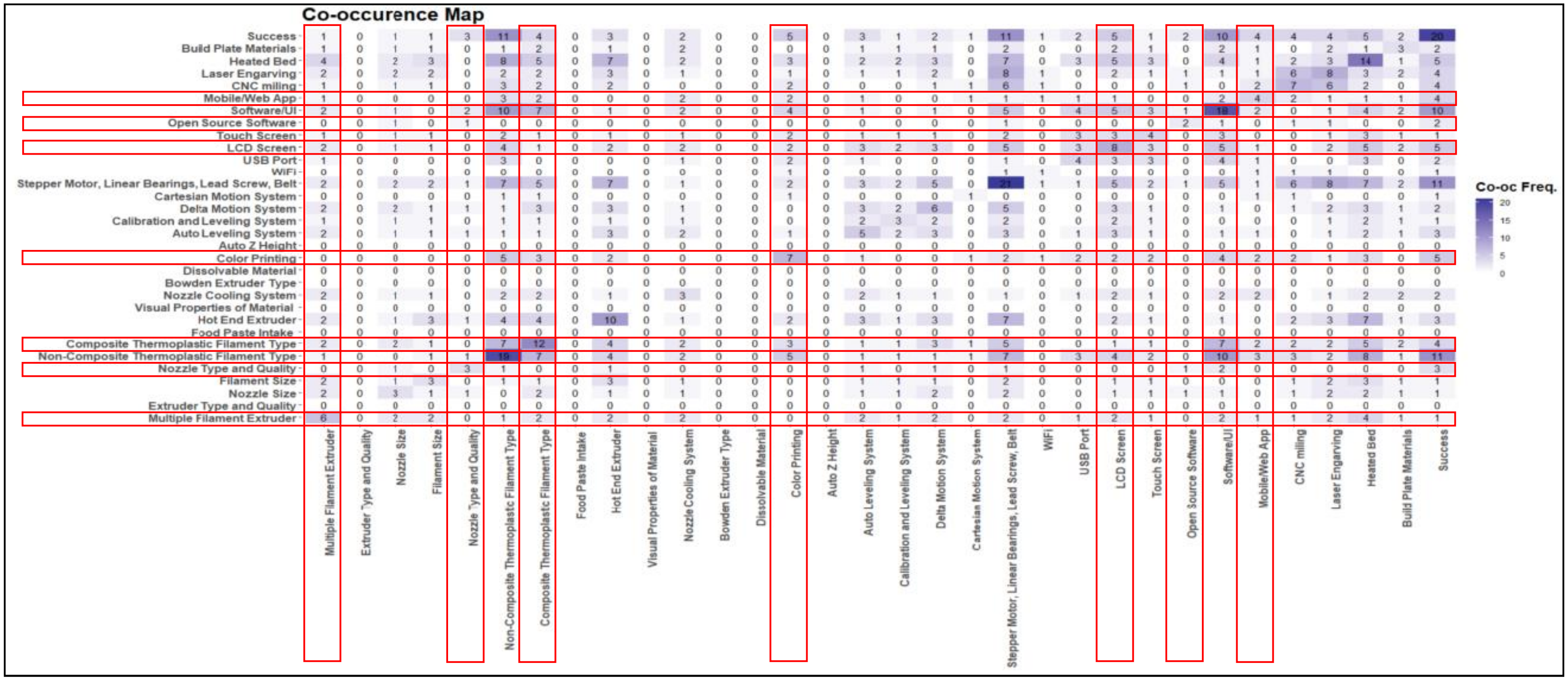

Figure 29 - Co-occurrence map of features of the material extrusion process for the "recent frugal" segment.

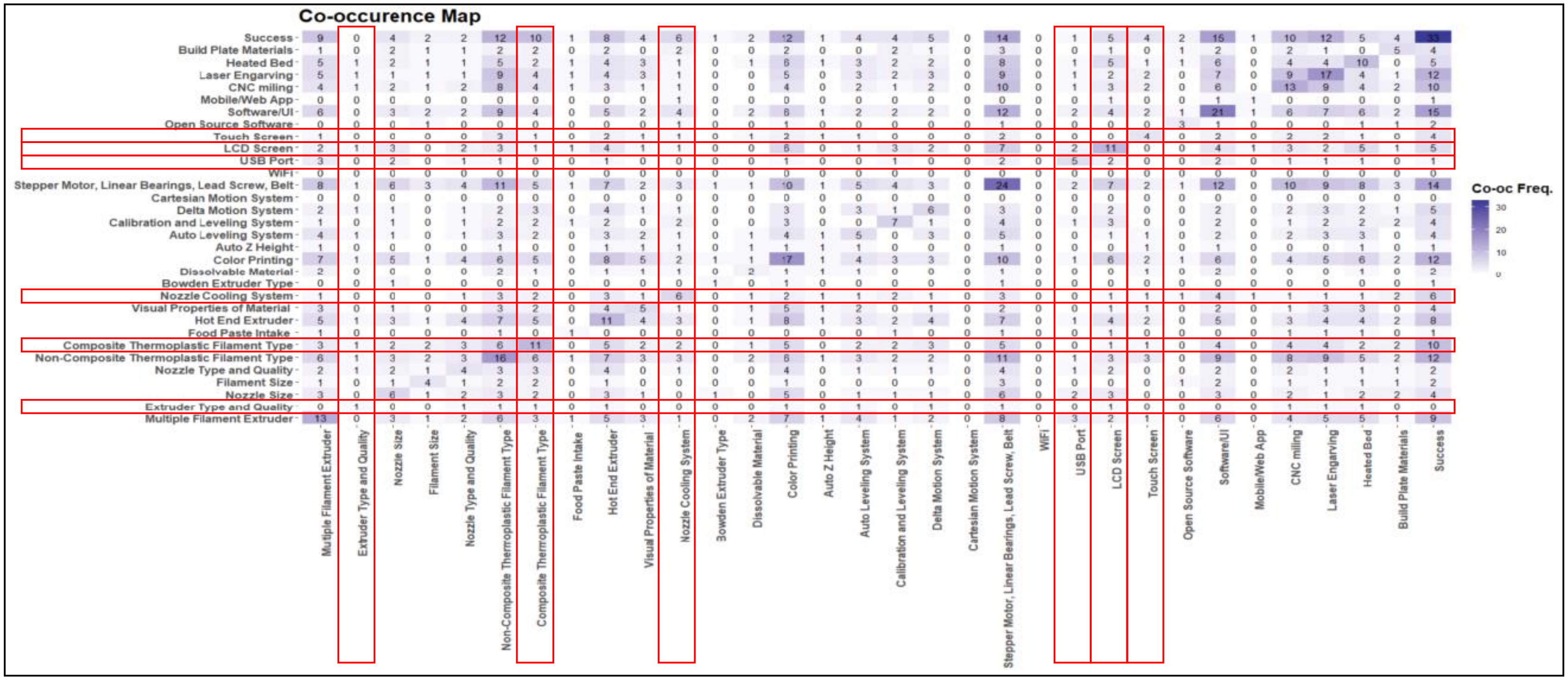

Figure 30 - Co-occurrence map of features of the material extrusion process for the "recent deep-pocket" segment.

5.2.6.1. Derived insights into relative advantages in the material extrusion process

The rest of this section discusses the derived insights from the analysis results of the material extrusion process. Two sets of results are considered for drawing insights—selected features and the probability of non-zero coefficients. Derived insights from the selected features in the various model have higher confidence. However, the performance of models with selected features suffers in some segments. If the selected features don't have the power to explain the entire projects in the segment, the accuracy can't be improved above the percentage of dominant outcome in the segment. Even with meaningful improvement in accuracy, the model can still suffer from imbalanced performance.

It is expected that segmentation harm the performance of the model more regarding aggravated dimensionality issue. Model performance is important in the "general" model since it intends to evaluate the impact of product features on the campaign's success in general. In contrast, a problem in model performance is not detrimental to confidence in the gained insight into relative advantages of a product. The selection of features provides confidence that there is a subset of projects in which selected features dominantly influence the outcome of a campaign. Although, the performance problem is considered in deriving insight itself. Whereas utilizing features with a non-zero likelihood of non-zero coefficient in drawing the insight lowers the confidence. As discussed above, the strength of association determines the probability of non-zero coefficients. The number of co-occurrence with other influential features affects the selection of features and consequently lowers the confidence in which features among co-occurred features impacting the outcome. However, the confidence in the effect of these features can be deduced if they are selected in other segments or can be verified by subject matter expert.

Comparing the result of the "general" classification model and classification model in various segments provides insights into relative advantages of products that elaborated in the rest of this section. Each relative advantage is marked as "statistically verified" and "verified by subject matter expert" to provide the source of confidence. The finding is labeled as "verified by subject matter expert" if it is based on comparing the impact of the features with a non-zero probability of non-zero coefficient and they are not selected in any segment. The findings based on comparing the effect of selected features or a mix of selected features and the features with a non-zero probability of non-zero coefficient are labeled as "statistically verified."

a) Product features influence backers' intention to support a technology product.

The result in the "general model"—Table 13—shows the impact of each product feature on the campaign's outcome. Therefore, product features influence the backers' intention to support a technology product. This finding is "statistically verified." The performance of the "general" classification model—section 5.2.2—is acceptable. Including product features significantly improves the accuracy of projects' classification—Table 15. Also, the classification model shows balanced performance in both failed and successful classes—Table 14 and Table 15.

b) Technology maturation impacts the innovative pattern of the product.

As discussed in the diffusion of innovation theory, the product loses its innovativeness and features attraction decline as new features become mainstream over time. As section 5.2.3 shows, there is a detected "main design" space for projects before 2015—maturation point. In contrast, projects after the maturation point don't have a general development trend with only one strong branch development. Although maturation doesn't significantly affect the average success rate of projects, technology development becomes unconsolidated after maturation.

"Color Printing," " Bowden Extruder Type," " Composite Thermoplastic Filament Type," and "Nozzle Cooling System" are the breakthrough features selected in the "general" model with the strongest positive impact on the success of a project—Table 13. The results show that features are widespread distinctive features in the "deep-pocket" segment—Table 21— as well as in the "early" segment—Table 16—except "Nozzle Cooling System," which has a stronger impact in the "recent" segment—Table 16. This trend shows that as the technology matures, introducing new features at premium prices gets slimmer. For instance, "Nozzle Cooling System" is an opportunity created by issues in earlier products discussed further in the following item. Also, product maturity either eliminates the interest or makes them weaker in breakthrough features that strongly impact the "early" segment. This insight is "statistically validated."

c) Issues of "early" products can strengthen the interest in a feature.

Item b) discusses the opportunity created by the "early" products issues. The "Nozzle Cooling System" shows influence in the "general" model—Table 13—and "deep-pocket" segment—Table 21—but not in the "early" or "recent" segment. Figure 31 shows that the association of the "Nozzle Cooling System" with the campaign's success varies throughout the "early" segment. However, the association with the successful campaign gets stronger in the "recent" segment, indicating the strengthened needs in a robust nozzle. The need for the robust nozzle grows because of the easily clogged nozzle due to temperature change or handling of different filament types.

Other trends similar to the "Nozzle Cooling System" are detected, although they aren't as strong as the "Nozzle Cooling System." In the "early" phase, "Multiple Filament Extruder" is enabled multi-color printing and multi-material part vs. support structure printing. However, complexity in hardware and software led to poor quality printers in practice with high downtime. Early issues with nozzle clogging and print disruptions generate the need for remote surveillance of the print process. Mobile applications provide a user-friendly experience by allowing users to remotely supervise long-hour printing jobs, check the print processes at any time, and stop the extruding process in case of a problem or even shut off the device if needed. The positive attitude toward "Multiple Filament Extruder" is shown in the "early" segment result—Table 16. In contrast, the concern for "Multiple Filament Extruder" and the need for "Mobile/Web App" is strongly sensed in the "recent frugal" segment—Table 27. This insight is "statistically validated."

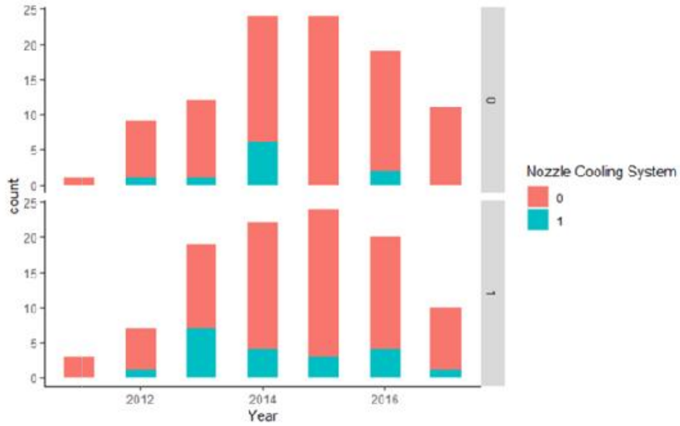

Figure 31 - Existence of "Nozzle Cooling System" in successful and failed projects from 2011 to 2017.

d) Provided discounts on crowdfunding platforms for pre-selling is considered an incentive for backers' support. Although, backers are not necessarily looking into finding the cheap product. A lower price becomes an incentive, in some cases, for continued interest in "early" breakthroughs after the maturity point.

The chance of success in the "frugal" segment is 46% in both "early" and "recent" segments. On the other hand, the success rate in the "deep-pocket" segment is 69% and 66% in "early" and "recent" segments, respectively. A higher success rate in the "deep-pocket" segment indicates a stronger incentive to support the project than the product's price. Breakthrough features such as "Composite Thermoplastic Filament Type" and "Color Printing" besides higher quality and reliability of extrusion system performance including "Nozzle Cooling System" and "Bowden Extruder Type" are appealing enough among "deep-pocket" backers to pay a premium for these features—Table 21. "Composite Thermoplastic filament type" is the only feature that shows impact in all four segments to some degree. The positive impact of "Composite Thermoplastic Filament Type" becomes negative from "early frugal"—Figure 22—to "recent frugal"—Figure

24—segment. This change indicates either the demand saturation for feature or reliability and quality concern stemmed from negative experiences in the "early" phase.

In contrast, the positive impact is carried from "early deep-pocket"—Figure 23— to "recent deep-pocket"—Figure 25—segment. Although, the overall impact declines in the "recent deep-pocket" segment—Figure 25. As the feature's existence grows over time, its association with the unsuccessful campaign—Table 40 also grows, which lowers the overall impact of the feature. These results indicate that there's still interest in this feature yet smaller.

On the other hand, "'Color printing" is the breakthrough feature that shows a positive impact in the "early deep-pocket" segment—Figure 23— and "recent frugal"—Figure 24—segments. The weaker positive impact in the "recent frugal" segment is an indication that this feature can be delivered at a lower price. It can also indicate a new market, including hobby sing and artistic and creative people that are not looking for a high price tag, super high-quality printer. Although the insight is drawn from the probability of non-zero coefficients, it is considered "statistically validated" since discussed features are selected in the "general" model and some segments.

e) Standardization kills the interest in a feature.

"Filament Size" only shows the impact on the campaign's success in the "early" segment—Table 16. "Filament Size" is an essential part of 3D printers, and interest in the feature shows the backers' preference. Interest in "Filament Size" in the "early" segment indicates that sizes are varied early on. Thus, setting an industry standard for "Filament

Size"—1.75mm or 2.85 mm—is eliminated interest in the feature. This insight is "statistically validated."

f) Emerging winner of competing systems.

"Bowden Extruder System" is considered separately from other types of extruders—grouped as "Extruder Type and Quality"—due to its importance. The likelihood of non-zero coefficients of the "Bowden Extruder System" is higher in the "general" model—Figure 14—than in the "early" segment—Figure 15—and has zero likelihood in the "recent" segment—Figure 16. In the "early" segment, the feature has a higher frequency but a lower association with the campaign's success compared to the "recent" segment—Table 40. The decline in frequency may follow the overall project decline in the "recent" segment—. A higher association with a successful campaign can recognize its higher performance and reliability concerning other extruding systems.

Another example is the interface trend. "USB Port" shows more popularity rather than "Open Source Software" in the "early frugal" segment—Figure 22. It is custom to have propriety software and open-source software in the early stages, which is perceived as low support and a low-quality approach. However, perfecting both hardware and developing a brand new proprietary software set many innovators for failure. The non-zero likelihood of "Open Source Software" in the "recent frugal" segment—Figure 24—reveals that the non-proprietary approach gains more ground later. Figure 25 shows that "USB Port" loses the initial popularity and negatively impacts the success of later high-end products—the "recent deep-pocket" segment. In the later stage, most innovators focused on the hardware while taking advantage of high quality and well-adopted open software for pre-processing such as slicing. This insight is "verified by subject matter expert."

g) There is interest in essential/must-have features when quality is a concern, especially for a product with a lower price.

The "Nozzle Type and Quality" is considered a fundamental feature compared to "Composite Thermoplastic Filament Type" and "Color Printing." The result indicates that the "frugal" backers are interested in the "Nozzle Type and Quality" feature—Table 21—in both the "early " and "recent" segments—Figure 22 and Figure 24. The impact of the "Nozzle type and quality" feature increases in the "recent" segment—Table 27—as well as other features including "Multiple Filament Extruder" and "Mobile/Web App," which gained attention to deal with known technical issues related to the nozzle, as discussed in item c). These factors indicate the importance of assuring quality in the "frugal" segment and the expectation toward basic 3D printers to deliver a stable and user-friendly experience at a lower price. Although, unbalances in the performance of the "frugal" segment model—Table 23—suggests that quality is not the only factor influencing the "frugal" segment backers' decision. This insight is "statistically validated."

h) Breakthrough features are the main attraction.

All the features that have a significant positive effect on campaign success are new features or systems. They mostly present in "deep-pocket" and "early" segments—Table 16 and Table 21—that show backers' willingness to pay a premium for these features in the "early" phase. Other features show a non-zero likelihood of impact on the campaign's success at the cross-section of these segments ("early deep-pocket"). Although, their impact is not as strong as the features, including "Composite Thermoplastic filament type" and "Color printing"—Figure 23. Other weak trends in the "early deep-pocket" segment are related to dealing with warping and shrinkage problems—"Heated Bed," "build Plate"—, print precision—"Auto Leveling"—,and interface—"LCD Screen," " Open Source Software."

In a nutshell, breakthrough features are the main advantage of 3D printer products using the material extrusion process. Backers are willing to pay a premium for products with breakthrough features. However, breakthrough features become mainstream over time and lose their impact. Regarding the relatively new concept of desktop 3D printer, there is also an interest in the basic product with decent quality. Besides, the developmental process affects complexity, experienced problems, and industry standard. When the industry sets a standard for a feature, its impact on the campaign's success diminishes. Also, winner practice among various comparable approaches gets chosen in the developmental process. Moreover, the development process creates uncertainty toward a specific possibility. For instance, when complexity negatively impacts the quality, backers don't trust it can be delivered at a lower price point, and price becomes a weaker incentive.

5.3. The vat photopolymerization process analysis

The number of projects associated with the vat photopolymerization process is about one-fourth of the number of material extrusion projects. Besides, as shown in Figure 32, the project distribution pattern doesn't quite follow the maturity or s-curve. The total number of projects ranges from 6 to 11, with the highest success rate in 2016.

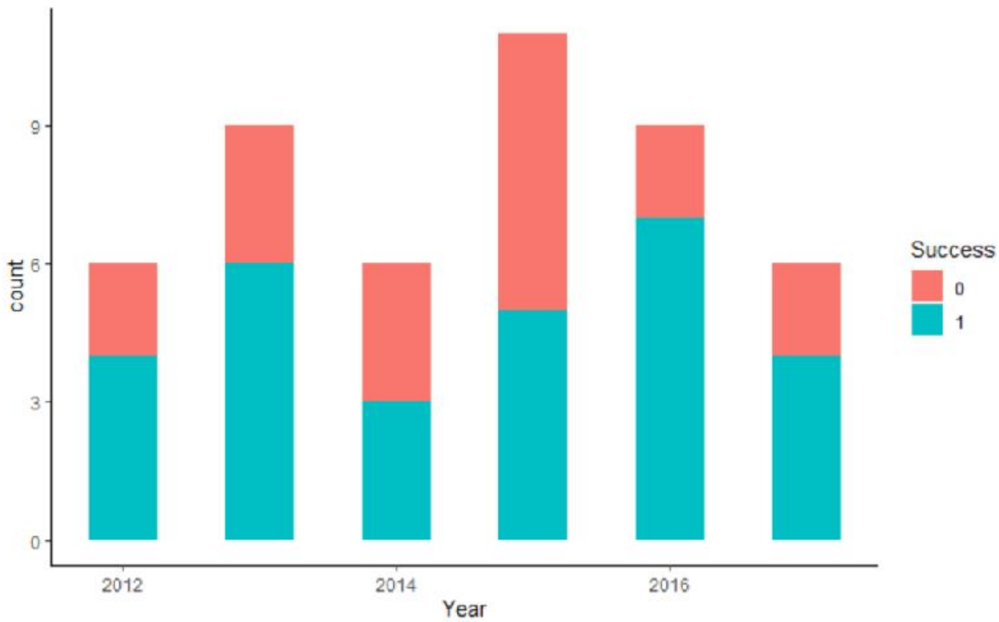

Figure 32 - Vat photopolymerization 3D printer's project distribution from 2011-2017.

The vat photopolymerization process uses a light source to solidify successive layers on a surface or base of a vat liquid photopolymer. Several distinct technologies use the same method of solidifying liquid. The variation in technologies is due to the implemented source of the light and techniques to carry out the process. *Stereolithography (SLA)* and *digital light processing (DLP)* are examples of 3D printer technologies using the vat photopolymerization process.

SLA uses a computer-controlled laser beam to build objects within a tank of liquid photopolymer. There are two different ways to print objects using this technology. One way is forming the object on a perforated build platform, which is initially positioned under the surface of the photopolymer vat and use the UV beam to cure the object layer on the surface of the liquid and then lower the build platform to cure the next layer. Some small SLA 3D printers use the inverted process in which the object is built on the bottom of the build platform in constant contact with the liquid. After curing the layer, the build platform is raised to cure the next layer. Objects built by the SLA technology sometimes require post-print finishing, such as removing the support structure by hand or tool, washing by solvent and water, or curing the object in a UV oven. Also, one required step for items created in the transparent resin is varnishing to prevent discoloration. Occasionally, the surface quality needs improvement, which can be done by blasting the surface with glass beads or polishing the surface by vapor honing.

Digital light processing (DLP) follows the same configuration as inverted stereolithography, where the laser is replaced with the DLP projector. DLP panels feature a tiny imaging chip that contains an array of microscopic mirrors or Digital Micromirror Devices (DMDs). Controlling and rapidly rotating DMDs reflect light out of the projector lens or onto the heatsink to create a high-quality image for projection. DLP solidifies each object layer by projecting the image rather than tracing the outline of each layer with a laser.

5.3.1. The vat photopolymerization process feature categories

The product features used in analyzing the vat photopolymerization process are related to resin type, resin reservoir system, light system, camera system, projection system, support structure, and interface. Product feature categories related to each technological trend are included in Table 41. The existence ratio of product feature categories, as shown in Figure 33, illustrates the prevalence of each category and the focus on each technological trend.

Product Feature categories	Technological Trend
Resin Options	Resin Type
Resin Color Options	Resin Type
Curing Time	Resin Type
Composite Resin	Resin Type
Resin Tank Volume	Resin Reservoir System
Tank Heater	Resin Reservoir System
UV Laser	Light System
UV Lamp	Light System
Photomask	Light System
Sublayer Photocuring	Light System
High Definition Projector	Projection System
Projector Lens	Projection System
Projectorless Option	Projection System
Projector Size	Projection System
Optical Lens	Projection System
Optical Breadboard	Projection System
Optical Power	Projection System
Optical Sensor	Projection System
Fresnel Lens	Projection System
Lens	Projection System
Camera System	Camera System
Support Polymer	Support Structure
USB Port	Interface
LCD Screen	Interface
Touch Screen	Interface
Open Source Software	Interface
Software, UI	Interface
Mobile Web App	Interface

Table 41 - Product feature categories paired with the technological trend in the vat photopolymerization process.

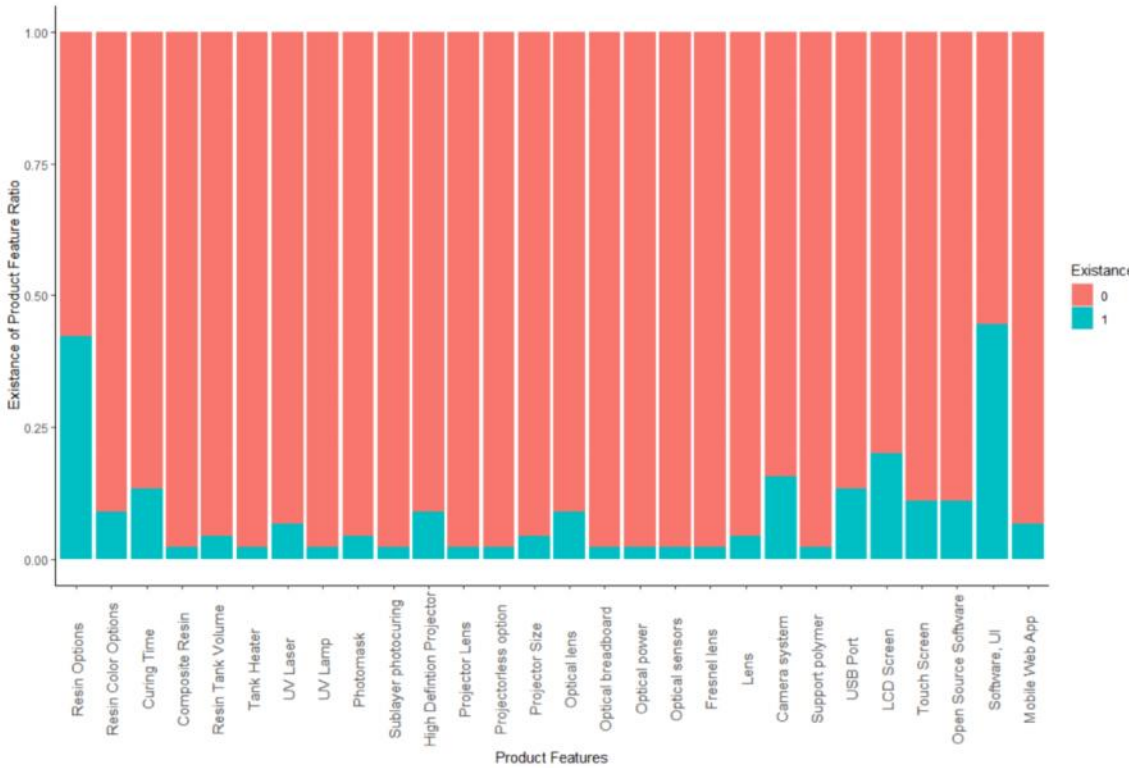

Figure 33 - Product features existence ratio for the vat photopolymerization process.

5.3.2. The effect of features of 3D printers using the vat photopolymerization process on the success of the campaign

As discussed in section 5.1, the vat photopolymerization uses a different process rather than material extrusion. So, it is expected that 3D printers using vat photopolymerization process have different product features except for interfaces. Table 42 shows the result of the classification model with product feature categories for the vat photopolymerization process as independent variables and the campaign's success as an outcome of the model. As opposed to the material extrusion process, there is no dominant design space that can explain the success of the vat photopolymerization process projects.

Product Features	Dependent variable: Success (Optimal λ = 0.1391331)
Resin Options1	0
Resin Color Options1	0
Curing Time1	0
Composite Resin1	0
Resin Tank Volume1	0
Tank Heater1	0
UV Laser1	0
UV Lamp1	0
Photomask1	0
Sublayer Photocuring1	0
High Definition Projector1	0
Projector Lens1	0
Projectorless Option1	0
Projector Size1	0
Optical Lens1	0
Optical Breadboard1	0
Optical Power1	0
Optical Sensor1	0
Fresnel Lens1	0
Lens1	0
Camera System1	0
Support Polymer1	0
USB Port1	0
LCD Screen1	0
Touch Screen1	0
Open Source Software1	0
Software, UI1	0
Mobile/Web App1	0
Intercept	0.5947071

Table 42 - "general" classification model result considering product features as independent variables and success of the campaign as the dependent variable—vat photopolymerization process.

The overall success of the vat photopolymerization process is about 64%. In this case, product features add no significant information to increase the accuracy of predicting the success of projects. Table 43 and Table 44 show that the model outcome is biased toward the successful class. The low number of projects on the Kickstarter platform and the lack of dominant technological trends skew the results toward the dominant class—the successful class.

	Successful (1)	Failed (0)
Successful (1)	29	16
Failed (0)	0	0

Table 43 - Confusion matrix for the "general" model—vat photopolymerization.

Positive Class: 1	
Accuracy	0.6444
95% CI	(0.4878, 0.7813)
No Information Rate	0.6444
P-Value [ACC > NTR]	0.567565
Mcnemar's Test P-Value	0.0001768
Sensitivity	1
Specificity	0
POS Pred Value	0.6444
Neg Pred Value	-
Prevalence	0.6444
Detection Rate	0.6444
Detection Prevalence	1
Balanced Accuracy	0.5

Table 44 - Confusion statistics for the "general" model—vat photopolymerization.

Despite no selected features, Figure 34 shows that product features impact the success of a campaign in some iterations. The absence of strong trends and a low number of projects provides an opportunity to even less frequent features to show an effect on project success. Section 5.2.6 elaborates on the circumstances in which features have a non-zero likelihood of non-zero coefficients and show a high or low likelihood. Section 5.3.5 discusses the insights drawn from the non-zero likelihood of product features' impact and their strength.

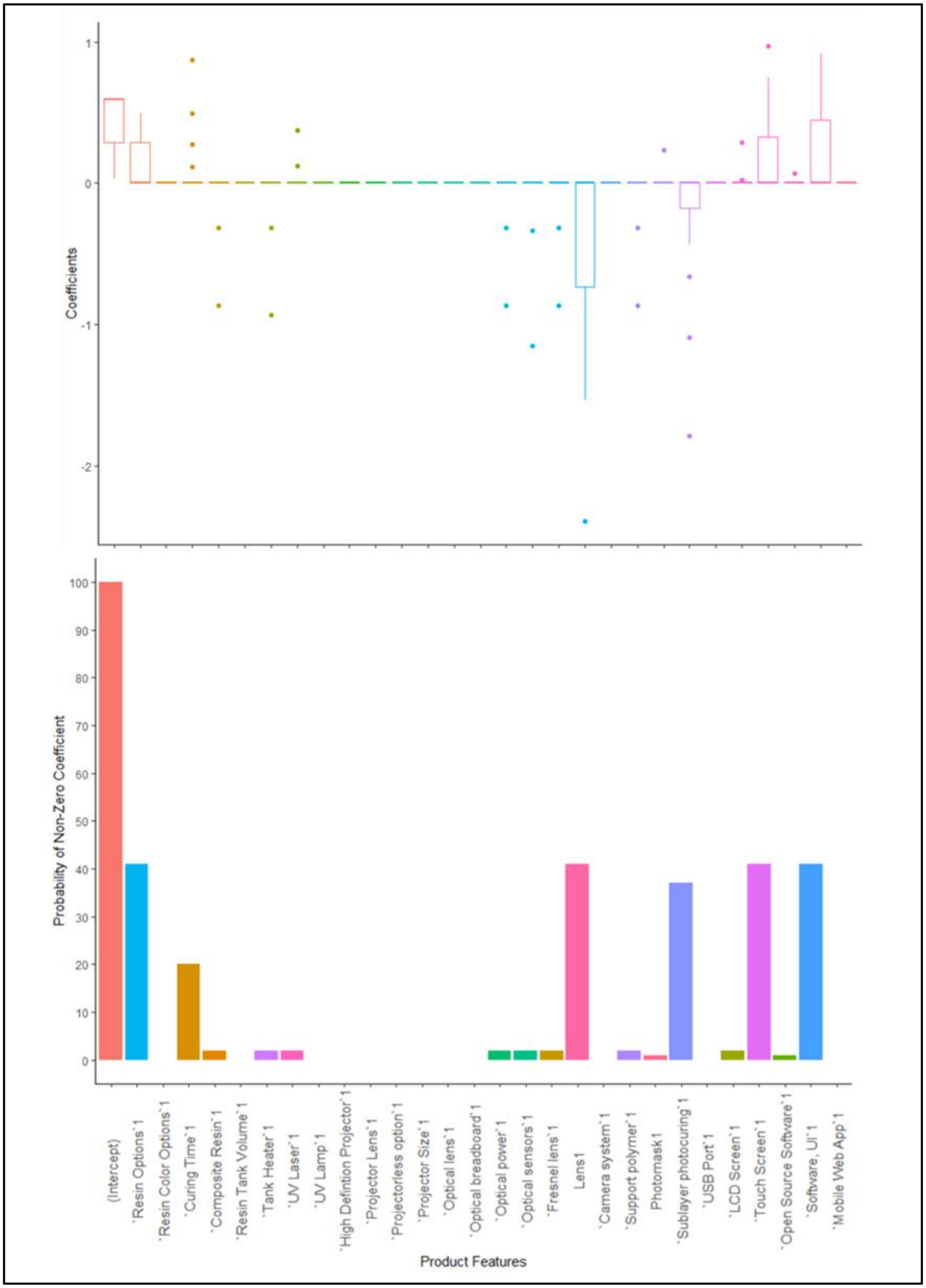

Figure 34 - Coefficient range and probability of a non-zero coefficient of vat photopolymerization process's features over 100 iterations—"general" model.

5.3.3. Time segmentation

Due to the low amount of projects, it is not feasible to carry time segmentation analysis for the vat photopolymerization process.

5.3.4. Price segmentation

Due to the low amount of projects, it is not feasible to carry price segmentation analysis for the vat photopolymerization process.

5.3.5. The vat photopolymerization process analysis results

The development of the vat photopolymerization process is slower than the material extrusion process. There are 45 projects from 2011 to 2017 with an overall success rate of around 64%. However, the success rate isn't uniform throughout the year, with a lower success rate in 2014 and 2015—Figure 32. No feature is selected in the "general" model—Table 42—that indicates the novelty of the product itself driving the interest, and there are no dominant technological trends for this process. Figure 34 illustrates lots of weak trends affecting the outcome of a campaign. Although, the trends in Figure 34 are not reliable. For instance, as shown in Table 45, "Camera System" has a high association with the campaign's success and relatively high frequency. The reason for having zero probability of non-zero coefficients is that all the "Camera System" feature co-occurs with the "Software/UI" feature—Figure 35—and "Software/UI" masks the impact of "Camera System." Also, the features mentioned once have a perfect association with either success or failure of a campaign. If they don't co-occur with any other influential features, they show a non-zero probability of impact—though very slim.

Product Features	Freq.	Probability of Existence in Successful Campaign	Probability of Existence in Failed Campaign	Ratio of the probability of Existence in Successful to Failed Campaign
Software/UI	20	0.5517	0.25	2.2069
Resin Options	19	0.5172	0.25	2.0690
LCD Screen	9	0.2414	0.125	1.931
Camera System	7	0.2069	0.0625	3.3103
Curing Time	6	0.1724	0.625	2.7586
USB Port	6	0.1379	0.125	1.1034
Touch Screen	5	0.1724	0	Inf.
Open Source Software	5	0.1379	0.625	2.2069
Resin Color Options	4	0.1034	0.0625	1.6552
High Definition Projector	4	0.0690	0.125	0.5517
Optical Lens	4	0.0690	0.125	0.5517
UV Laser	3	0.1034	0	Inf.
Mobile/Web App	3	0.1034	0	Inf.
Resin Tank Volume	2	0.0345	0.0625	0.5517
Projector Size	2	0.0345	0.0625	0.5517
Lens	2	0	0.0125	0
Photomask	2	0.0690	0	Inf.
Composite Resin	1	0	0.0625	0
Tank Heater	1	0	0.0625	0
UV Lamp	1	0.0345	0	Inf.
Sublayer Photocuring	1	0	0.0625	0
Projector Lens	1	0.0345	0	Inf.
Projectorless Option	1	0.0345	0	Inf.
Optical Breadboard	1	0	0.0625	0
Optical Power	1	0	0.0625	0
Optical Sensor	1	0	0.0625	0
Fresnel Lens	1	0	0.0625	0
Support Polymer	1	0	0.0625	0

Table 45 - Metrics of features of the vat photopolymerization process.

Even though there is no feature selected in Table 42, it doesn't reject the impact of product features on the campaign's success. As discussed before, the curse of dimensionality, low amount of data, and absence of dominant trend result in no selection. Trends in Figure 34 are not reliable to build confidence in the advantage of the product, but it shows that product features impact the success of a campaign in the subset of projects. It also reveals the close attention the interface is received in the vat photopolymerization process. It also highlights the usefulness of analysis in the material extrusion process for technologies that their development is in the early phase.

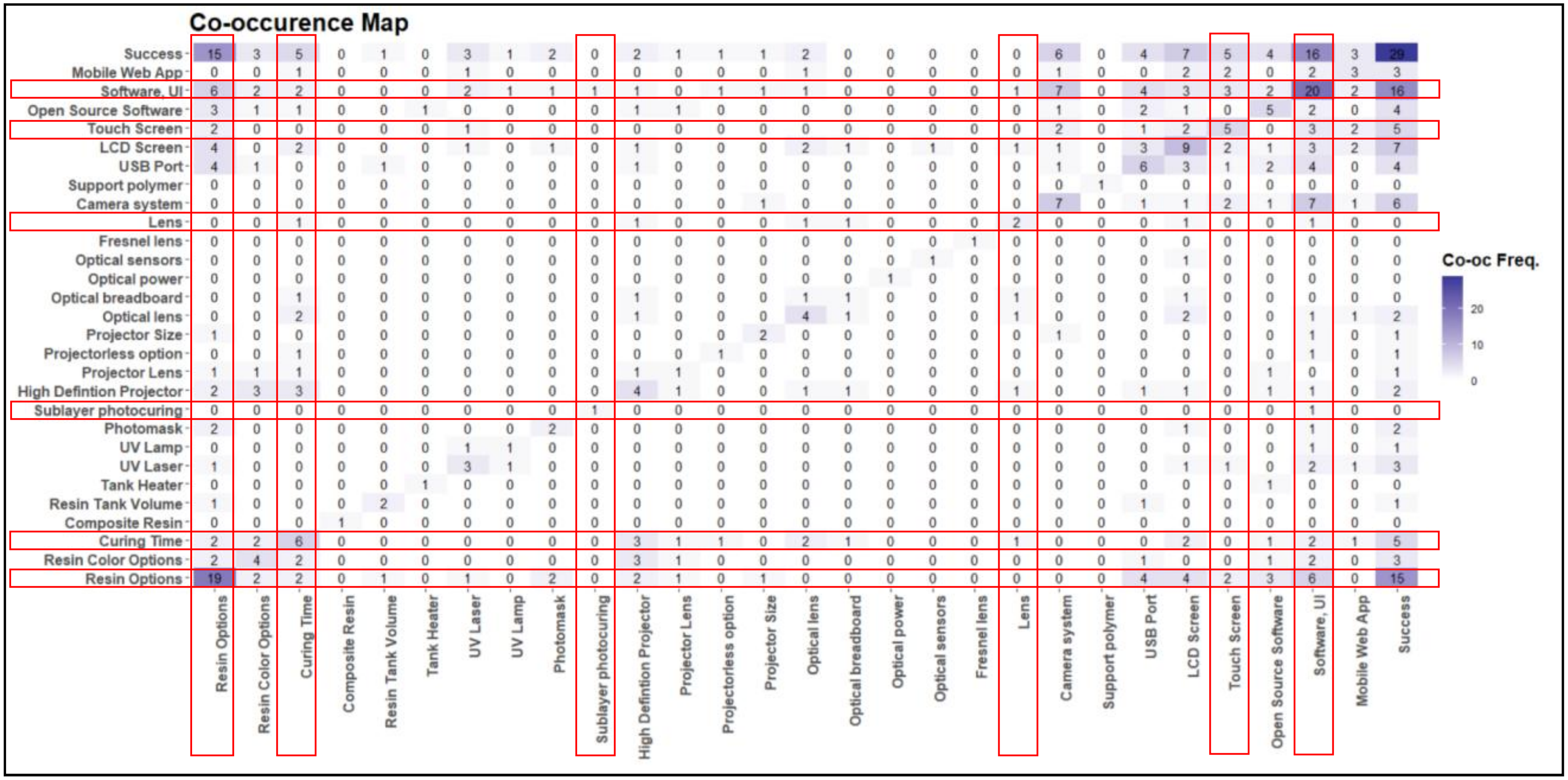

Figure 35 - Co-occurrence map of features of the vat photopolymerization process for the "general" market.

6. Discussion of results

This study intended to analyze the perceived value of technology products by backers in a crowdfunding environment. The emergence of crowdfunding platforms coincided with the expiration of the FDM patent that creates a suitable environment for developing desktop 3D printers at a lower price than commercial 3D printers. The relative abundance of 3D printer projects makes it a well-suited case for this study. 3D printer projects on Kickstarter from 2011 to 2017 are analyzed to answer research questions in this study, including:

1) Do principals of diffusions of innovation apply to the case of crowdfunding of technology products—with the focus on innovation element?
2) What are the relative advantages of technology products in the crowdfunding environment?

Chapter 5 discusses the effect of product features on the campaign's success, which is considered a proxy for backers' motivation to support. The analysis is divided based on the printing process. The fundamental product features differ from the material extrusion process to the vat photopolymerization process—two processes available on the Kickstarter platform. However, the amount of projects available in the vat photopolymerization process is far less than the material extrusion process, limiting the contribution of analysis of this process to the first question. The following sections discuss the result and sensitivity of analysis regarding each research question.

6.1. Do principals of diffusions of innovation apply to the case of crowdfunding of technology products—with the focus on innovation element?

The observed effect of product features on the success of a campaign is sensitive to multiple factors. One factor is the comprehensiveness of provided information for the product in the project description. This study assumes that highlighted features create value for the product. The visibility of products is one of the factors affecting the diffusion of innovation. The effect of incomplete information on the product resembles the product with lower visibility. The negative impact of incomplete information is acceptable and expected in this study. However, it is impossible to distinguish the effect of incomplete information from non-existence features. Another factor is the comprehensiveness of product features extracted from the project description. Utilizing the aspect extraction techniques provides powerful tools to cover more product features than an approach relying on subject matter expert suggestions. This study uses a network of co-occurred nouns to evaluate the double propagation result—employed extraction technique—regarding the comprehensiveness of generated pool of candidate product features—refer to Appendix C. There is one more factor related to preparing the product features. This study categorized the product features based on their functionalities. However, defined functionalities are not mutually exclusive. The width of categories is subject to change, whether combined or break down further. The analysis results are sensitive to the width of categories. The width of each category is decided based on the subject matter experts' suggestions and the provided insight concerning the availability of data. The categorization process is thoroughly documented in Appendix E to explain any contradictory results.

Previous research confirms the relationship between two principles of diffusion of innovation—communication channel and social system—and success of the crowdfunding campaign as discussed in Success determinants of crowdfunding campaigns. The result in the material extrusion process—section 5.2.2—shows a correlation between product features and campaigns' success. So, the innovation itself impacts the technology backers' decision to support a crowdfunding project. This relationship establishes that the innovation element is a success determinant in the crowdfunding environment. However, the result in the vat photopolymerization process—section 5.3.2—doesn't show a relation between product features and campaigns' success. This contradictory result does not undermine the effect of product features. It points out the sensitivity to dimensionality as discussed in The curse of dimensionality. The sensitivity of the analysis to the low number of cases and lack of dominant trend is further discussed in section 5.3.5. Although there are no dominant trends in the vat photopolymerization process, Figure 34 represents weaker trends and the relationship between product features and campaigns' success in a subset of the projects. The result of analysis in the vat photopolymerization process underscores the usefulness of insights gathered about the relative advantages of crowdfunding technology product from analysis in the material extrusion process—discussed in the section below.

6.2. What are the relative advantages of technology products in the crowdfunding environment?

In this work, segmentation is an adopted approach to learn about the relative advantages of technology products. Besides the sensitivity discussed above, segmentation thresholds also affect the findings related to the perceived value of products or their relative advantage. The threshold for both time and price is chosen in line with study goals and classification model performance. Also, the plausibility of findings is confirmed through subject matter experts. Another discussed concern is about the effect of estimation error in the price of products—section 4.2.2—on the result of a segmented classification model. It is shown in section 5.2.4 that model results are not sensitive to this estimation error.

According to the results discussed in the material extrusion process, section 5.2.6, three main factors give a product relative advantage at the top level: *novelty* (among all other product features), *novelty-price* dynamic, and *quality* improvement. A Counterintuitive finding of crowdfunding success cases in 3D printers indicated that higher prices were more associated with success than lower price products. That shows the user in technology segment of crowdfunding environment tends to prioritize novelty and premium features over price. In a crowdfunding environment, time affects the innovativeness of a product, similar to the diffusion of innovation theory. Once novel features become a commodity in later phases, a relatively lower price could moderately enhance the odds of success of the campaign. Although users do not have prior knowledge of the product's quality on a crowdfunding platform, such knowledge is accumulated for similar technologies over time. Prospect backers tend to positively receive new products that offer solutions to address those quality issues perceived by the community in the earlier products. Therefore, focusing on quality-improvement features and communicating that with prospect backers well increases the probability of success in the later phases (something that is not available to the early campaigns).

The relative advantages of products on the crowdfunding platforms are reasonably similar to the relative advantages of the product in the general market. The main differences are the availability of practical information and alternatives at the time of decision-making. These differences affect the information synthesis and decision-making process. In the general market, buyers compare the alternatives concerning the features, quality, and price and decide which product to buy. In contrast, crowdfunding backers are not optimizing their decision. They decide based on the general knowledge whether the product meets their needs and worth taking the risk. For instance, as observed, the sensitivity toward price is lower on crowdfunding platforms. Also, attitude toward quality is shaped based on practical knowledge available on an earlier product rather than the direct comparison between products.

Besides, the market size on the crowdfunding platform is limited compared to the general market. The limited market size makes a product mature faster. Novel products in the general market may not be considered novel on the crowdfunding platform. So, project founders should consider that failed campaigns do not necessarily mean a lack of demand. The demand for the product needs to be analyzed regarding the previously released campaign.

7. Limitations

This work comes with several limitations. These limitations are either related to inherent limitations related to crowdfunding context or the utilized methods.

7.1. Inherent limitations associated with processing textual information

The textual information preparation process is a combination of automatic and semi-automated approaches. The double propagation method is used to automate the extraction of a pool of product feature candidates. I have taken some steps to test the performance of double propagation results, including examining the adequacy of double propagation rules and candidate pool against frequent nouns' co-occurrence network. Then, I use a semi-automatic approach to detect the technologies, characteristics, systems, and processes of 3D printers from a pool of candidates and check their comprehensiveness with subject matter experts. Though the (semi-)automatic process has a significant advantage compared to the manual approach in detecting features of 3D printers, there is still a chance that either the extraction process or researcher missed a few characteristics.

Besides, with the help of a subject matter expert (SME), the functionalities of the 3D printer's features are defined, and noun phrases are categorized according to those functionalities. Sometimes not knowing the context creates ambiguity in the category that noun phrase belongs to. I created a web app that can show all the sentences, including a particular term, and help SME improve the accuracy of the categorization process. Categorization based on the functionality, ambiguity resolution, and comprehensive documentation of the categorization process aims to minimize the impact of categorization variations on findings. However, one factor that cannot be controlled is the depth of categories and product functionalities. If a functionality breaks down to a few sub-function or vice versa, it may change some of this study's findings.

7.2. Inherent limitations related to product features' description

The information provided on the crowdfunding platform is not consistent. Project initiators have different ideas about what product features are essential to be highlighted and included in the project description. Also, founders may use other places and mediums to provide information for their innovative products. For instance, some product features may be communicated in a campaign video, comment section, social media platforms, blogs, etc. This study only uses information in the title, summary, and description of crowdfunding projects, and it is blind to information provided through other mediums and places.

7.3. Battle of scarcity and validation

This study shows that product novelty is an essential motivation for backers and a success factor for a crowdfunding campaign. New added features or functionality bring novelty. However, it is hard to validate the effect of the new feature on backers' decision to support if there are very few cases that have the feature—either newly introduced or limited features. This study uses bootstrap techniques to provide a probability of influence—confidence—for the less frequent features. Though, the probability related to occurrence frequency might not be useful in newly introduced features.

7.4. Not considering other success determinants of crowdfunding campaign

This study only considers the effect of perceived attributes of a product. Other success factors are not taken into consideration. This work aims to establish a relationship between product features and the campaign's success and provide insight into the possible effects. Most of the literature about success factors focuses on building a model to predict the outcome of campaign. Though it is impractical to include the product features in predictive models to improve their accuracy, it can explain the unaccounted factors that lower the prediction performance. With the lack of analysis considering product features and other success factors simultaneously, it is hard to measure the significance of product features compared to other determinants.

7.5. Effect of the product development in the general market

The relative advantage of a product on crowdfunding is studied only concerning the product development on the platform. However, the product development trend off of crowdfunding platforms can affect the relative advantages of a product. The external development trends can affect the novelty, quality, and perceived value—required investment—of products on crowdfunding platforms.

8. Future research

Crowdfunding platforms provide a suitable environment for entrepreneurial activities. However, platforms' primary purpose is to enable alternative funding opportunities. Other potentials can enrich entrepreneurs' experiences like marketing, market research, and co-creation. Very little research, including this study, analyzes crowdfunding platforms from innovation-related perspectives. For instance, a research body focuses on utilizing online platforms and social media to identify the lead users and the new trend for product development purposes. There are few problems with using this online medium, such as social media. Trends on social media only show ideas, not practice, and provide no information on the demand for new trends. These problems can be addressed by switching to a crowdfunding platform.

Another potential future research is related to one of the limitations discussed above. Product development in the general market can affect the product development process on a crowdfunding platform. This effect hasn't been explored, providing an opportunity for future research.

9. Contributions

The main contribution of this work is to crowdfunding theory and a better understanding of crowdfunding dynamics. Yet, it contributes to aspect and opinion extraction methodology by applying it to a new field. It also contributes to entrepreneurial practices on crowdfunding platforms.

9.1. Theoretical contributions

1) *The perceived value of a technology product as backers' motivation*

There are general discussions about the crowdfunding backers' motivations. These discussions do not consider the characteristics differences between backers regarding crowdfunding platforms or activity types. Motivation such as altruism and recognition seems too simplistic for technology-savvy people to take a high amount of risk to support a project. It is expected that technology backers show more complex behavior since they are pledging a reasonably high amount of money to invest in a complex product. This study provides granular insights into the motivation of backers based on product and crowdfunding platform type. The relationship between product features and campaigns' success is established. This relationship indicates that the perceived value of the product impacts backers' interest to support a technology project.

2) *Product features as campaigns' success determinant*

The summary of success determinants of crowdfunding campaigns is provided in Table 1. As shown, the determinants are related to the campaign, founders' experience and influence level, the common interest of backers, community influence on backers, and social media's influence. There is one effort evaluating the importance of providing information about the product in the video and its impact on a campaign's success, especially in a technology product [22]. This is the first study that directly analyzes product features' impact on campaign success and confirms technology product features as a crowdfunding success determinant.

3) ***New insights into how technology backers evaluate the value of a product in the crowdfunding environment***

This study shows the connection between the product features and campaigns' success and elaborates on what makes the product desirable for backers. The findings show that novelty or innovativeness of products is the main driver. However, innovative products lose their novelty through time, and other factors, including price and quality, create value for the product. It also shows that the development trend of technologies influences the value of the product.

9.2. Methodological contributions

4) ***First time applying aspect and opinion extraction techniques in a crowdfunding context***

The aspect and opinion extraction techniques are mostly applied to customer reviews. This is the first effort to use the extraction methods in the crowdfunding context. This work updates the dependency relations of the double propagation technique with universal dependencies. Performance of double propagation is evaluated regarding updated dependency relations. The performance is examined from three perspectives, including the adequacy of rules, the effectiveness of each dependency relation to detect the aspect and opinion, and the ability to eliminate noises during extraction.

5) Introducing categorization process for product features on crowdfunding platforms

Previous approaches used clustering techniques such as agglomerate hierarchical clustering, LDA, etc., to automate aspect and opinion clustering and achieve entity resolution. In this study, clustering aims to reduce the dimensionality by grouping the product features according to the associated functionality group. This approach automatically addresses the entity resolution. However, it is not feasible to automate the whole process. This work explains a new process using clustering techniques and subject matter expert for categorizing product features.

Using the double propagation technique helps extract a pool of feature and opinion candidates that accelerates the extraction process. The results are also more reliable and comprehensive than feature extraction based on subject matter experts' input. In contrast, an extensive pool of feature and opinion candidates makes the clustering challenging. The agglomerate hierarchical clustering groups the noun phrases based on character similarity. Grouping the noun phrases with similar words helps a researcher identify the technology's main characteristics, processes, and systems. It is infeasible to automate the rest of the process since most clustering is based on character and semantic similarity, which doesn't apply to functionality-based clustering. So, the rest of the process has been carried according to SME inputs.

6) Open-source double propagation technique code in r

The implementation of double propagation in python and java is available on Github. However, there is no r implementation of the technique. The *r* implementation can be found at *"https://github.com/nchaichi/DoublePropagation."* The current implementation updates the dependency relations based on the universal dependency relations and utilizes the *UDPipe r* package to perform POS tagging and dependency parsing.

9.3. Entrepreneurial implication

7) Providing blueprint to entrepreneur to use crowdfunding for market research and demand estimation for their product

Entrepreneurs can benefit from crowdfunding platforms beyond raising funds. One such benefit is testing the demand for their product. Though market research is one of the crowdfunding potentials, there is no guidance for creators on how to take advantage of it. This study fills the gap by providing insights into the perceived value of products for backers. The most important fact to consider is that failure of a campaign doesn't necessarily mean that there is no demand for the product. It may point to the saturation of the market on the crowdfunding platform. This study aims to make analysis transferable to enable future market analysis.

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Appendix A - An overview of crowdfunding success determinants

Citation	Determinants	Model and Methodology	State & Platform
Etter, Grossglauser, and Thiran 2013 [59]	**Campaign:** 1- Funding goal, 2- Lunch date, 3- Duration, 4- Final state, 5- Number of projects with co-backers, 6- Number and proportion of these projects whose campaign are successful, 7- Number of backers, 8- Number and proportion of first time backers. **External:** 9- Number of tweets, replies and retweets, 10- Number of users who tweeted, 11- Estimated number of backers.	**Money-based success prediction:** M1- predicting final state based on campaign determinate 1, 2, &3 using KNN classifier. M2- similar to M1 determinants using Markov chain. **Social success prediction:** M3 - predicting final state based on determinants 1, 3, 9, 10, & 11 using SVM. M4- predicting final state based on determinants 1, 3, 5, 6, 7, & 8 using SVM. M5- train SVM with 5,6,7&8 individually to predict campaign success. Then use 1, 3 and probability of success obtained using each of the four individual predictors to predict the campaign success.	Dynamic/ Kickstarter
Mitra and Gilbert 2014 [60]	**Campaign:** 1- project goal, 2- project duration, 3- no. pledge levels, 4- min. pledge, 5- featured, 6- video present, 7- video duration, 8- categories, 9- no. of updates, 10- no. of comments, 11- FB connected, 12- description text, 13- reward text.	**Phase I:** Build n-grams matrix from variables 12 & 13, filter n-grams matrix to gather general phrases. **Phase II (campaign success prediction):** M1- variable 1 to 11 using penalized logistic regression. M2- variable 1 to 11 and general phrase using penalized logistic regression. **Phase III (semantic analysis):** M3- general phrase using linguistic inquiry and word count (LIWC). M4- general phrase using word tree visualization.	Static/ Kickstarter
Greenberg et al. 2013 [61]	**Campaign:** 1- goal, 2- parent category, 3- reward count, 4-duration, 5- twitter connected, 6- HasVideo, 7- Facebook connected, 8- no. Facebook friends, 9- no. twitter followers, 10- no. sentences in description, 11- sentiment of project description.	**Phase I:** analyze the sentiment of project descriptions using Mashape text processing API. **Phase II (campaign success prediction):** M1- all determinants using decision trees (LMT, decision stump, J48, random forest, REP tree). M2- all determinants using SVM(radial basis, polynomial, & sigmoid kernel function). M3- all determinants using boosted decision trees.	Static/ Kickstarter
Chung and Lee 2015 [62]	Project features: 1- category, 2- duration, 3- goal, 4- no. of images, 5- no. of videos, 6- no. of FAQs, 7- no. of rewards, 8- SMOG grade of reward description, 9- SMOG grade of main page description, 10- no. of sentences in reward description, 11- no. of sentences in the main description of a project. User features: 12- distribution of the backed projects under the main categories, 13- no. of backed projects, 14- no. of created projects in the past, 15- no. comments that a user made in the past, 16- no. of websites linked in a user profile, 17- no. of Facebook friends that a user has, 18- Facebook, Twitter, and YouTube connectedness, 19- SMOG grade of bio description, 20- no. of sentences in bio description, 21- Interval between joining date and project lunch date, 22- success rate of backed projects, 23- success rate of created projects. Temporal features: 24- cumulated pledged money over time, 25- cumulated no. of backers over time. Twitter features: 26- no. of tweets, 27- no. of followings, 28- no. of followers, 29- no. of favorites, 30- no. of lists, 31- no. of tweets posted during the campaign, 32- no. of tweets containing "Kickstarter", 33- SMOG grade of aggregated tweets during campagin	KS Statistic: variables 1 to 23. Temporal: variables 24 to 25. Twitter: variables 26 to 33. M1- KS utilizing naive bayes to predict project success. M2- KS utilizing random forest to predict project success. M3- KS utilizing AdaboostM1 with random forest to predict project success. M4- KS + Twitter utilizing naive bayes to predict project success. M5- KS + Twitter utilizing random forest to predict project success. M6- KS + Twitter utilizing AdaboostM1 with random forest to predict project success. M7- KS+ Temporal utilizing AdaboostM1 with random forest to predict project success. M8- KS+ Temporal + Twitter utilizing AdaboostM1 with random forest to predict project success. /1 model predict two classes pledged money. /2 model predict three classes pledged money M9/1&2- KS utilizing naive bayes to predict project class of pledged money. M10/1&2- KS utilizing random forest to predict class of pledged money. M11/1&2- KS utilizing AdaboostM1 with random forest to predict project class of pledged money. M12/1&2- KS + Twitter utilizing naive bayes to predict project class of pledged money. M13/1&2- KS + Twitter utilizing random forest to predict project class of pledged money. M14/1&2- KS + Twitter utilizing AdaboostM1 with random forest to predict project class of pledged money. M15/1&2- KS+ Temporal utilizing AdaboostM1 with random forest to predict project class of pledged money. M6/1&2- KS+ Temporal + Twitter utilizing AdaboostM1 with random forest to predict project class of pledged money.	Static & Dynamic/ Kickstarter
Rao et al. 2014 [63]	1- duration, 2- funding goal, 3- launched time, 4-category, 5- cumulated pledged money over time.	M1- all variables utilizing conditional interference tree to predict project success.	Dynamic/ Kickstarter

Citation	Determinants	Model and Methodology	State & Platform
Crosetto and Regner 2014 [64]	Campaign: 1- duration, 2- goal, 3-featured, 4- no. of words in project description, 5- video count, 6- image count, 7- blog entries, 8- categories Pledge: 9- no. of pledger, 10- date and time of pledge, 11- amount pledged, 12- IsDonation, 13- IsPreSelling	Phase I: M1- campaign variables utilizing probit regression predicts project success in fan phase. M2- campaign variables utilizing probit regression predicts project success in funding phase. M3- dynamic project categorization based on trend of pledge over time and use approach similar to (Greenberg et al. 2013) to predict each categories' project success. Though there is no explanation on the predication method. M4 - Descriptive analysis of pledge data to estimate the success based on dynamic categories.	Static/ Startnext
Du et al. 2015 [65]	1- goal, 2- duration, 3- FB connected, 4- no. of Facebook Freinds, 5- HasImage, 6- HasVideo, 7-NumRewards, 8- Year, 9- Category, 10- numWords in project description, 11- FOG index of project description, 12- NumCreated, 13- NumBacked	M1- using variables 1 to 9 and utilizing logistic regression predicts the project success. M2- using variables 1 to 13 and utilizing logistic regression predicts the project success.	Static/ Kickstarter
Xu et al. 2014 [66]	Projects' updates text, **Project update theme**: 2- ratio of update theme to the no. of updates. **Project presentation**: 3- no. of words in project title, 4- no. of words in project description, 5- number of URLs, 6- no. of images, 7- no. of videos, 8- readability of project description (Flesch ease score). **Update presentation:** 9- no. of words in update title, 10- no. of words in updates, 11- number of URLs, 12- no. of images, 13- no. of videos, 14- readability of update description (Flesch ease score). **Update time:** 15- update theme block is ratio of no. of updates in campaign phase (initial, middle, and final) to total no of updates for each theme. **Control variables:** 16- category, 17- duration, 18- goal.	**Phase I (discover themes) steps:** 1- collecting sample data, 2- cleaning the data, 3- creating bag of words, 4- decompose the updates into sentences and utilize Latent Dirichlet Allocation(LDA) to discover the themes. 5- experts refined the output of LDA to finalize unique theme and assigned category label to each theme, 6- creating dictionary by assigning words to each category based on LDA results, 7- verify the reliability of the produced taxonomy using two coders, 8- assign themes to updates, 9- analyze the distribution of update themes over time. **Phase II (association between updates & success):** Using variables 1 to 18 and feeding them block by block to hierarchical logistic regression to predict the project success.	Static&Semi-Dynamic/ Kickstarter
Tran et al. 2016 [67]	Same variables and analysis as [62] plus: 1- duration, 2- goal, 3- no. of images, 4- no. of videos, 5- no. of FAQs, 6-no. of reward, 7- no. of updates, 8- smog_reward, 9- no. of reward_sentence, 10- no. of main_sentence, 11- smog_main, 12-no. of bio_sentence, 13- smog_bio, 14- cumulated pledged money over time	M1- extracting two consecutive projects based on same idea and cluster them into fail_to_success and fail_to _fail group then calculate and compare the average rate of change for variables 1 to 13 in each group. M2- use variable 14 and utilize GMM-based clustering to cluster successful projects into cluster with the same pattern of cumulative pledged money over time.	Static&Dynamic/ Kickstarter
Zvilichovsky, Inbar, and Barzilay 2015 [8]	1- logged goal, 2- duration, 3- category, **Project attributes**: 4- NumRewardCategory, 5- HasLimitedCategory, 6- HasVideo, **Owners attributes:** 7- HadCreated, 8- NumPrevCreated, 9- HadCreatedAndSucceeded, 10- HadCreatedAndNeverSucceeded, **OwnersProjBackinginfo:** 11- NumPrevBacked, 12- HadBacked **Binary variable:** 13- TargetHadBacked, 14- SourceSucceded, 15- IsTargetSameCatAsSource, 16- IsTargetSameSizeAsSource	M1- variables 1 to 11 utilizing linear regression to predict the project success. M2- variable 1 to 12 utilizing binary logistic regression model to predict project success considering all gathered projects. M3to23- variable 1 to 12 utilizing binary logistic regression model to predict project success considering different set of data refined based on binary variable.	Static/ Kicksatrter
Mollick 2014 [16]	1- log(goal), 2- duration, 3- category, 4- IsFeatured, 5- HasVideo, 6- QuickUpdate, 7- SpellingError, 8- log(no. of FB Friends), 9- FBF lower 25%, 10- FBF 25%-50%, 11- FBF 50%-75%, 12- FBF top 25%, , 13- distance, 14- artists, 15- log(proximity to funders), 16- peers, 17- no. of FB freinds, 18- log(percent funded), 19- no. of backers, 20- category: graphic design, 21- category: software, 22- category: hardware, 23- category: product design, 24- category: technology	M1- variable 1 to 4 utilizing logistic regression to predict project success. M2- variable 1 to 4 & 8 utilizing logistic regression to predict project success. M3- variable 1 to 6 utilizing logistic regression to predict project success. M4- variable 1 to 4 & 7 utilizing logistic regression to predict project success. M5- variable 1 to 8 utilizing logistic regression to predict project success. M6- variable 1 to 7 & 9 to 12 utilizing logistic regression to predict project success. M7 to 12- variable 1 to 2 & 13 to 17 utilizing logistic regression to predict project success considering different sample of projects. M13- variable 1 & 20 to 24 utilizing Cox proportional hazard model to predict the degree of delay. M14- variable 1 & 18 & 20 to 24 utilizing Cox proportional hazard model to predict the degree of delay. M15- variable 1 & 18 to 24 utilizing Cox proportional hazard model to predict the degree of delay.	Static/ Kickstarter

Citation	Determinants	Model and Methodology	State & Platform
K. Chen et al. 2013 [68]	1- cumulative pledged money over time, 2- no. of projects backed by creator, 3- no. of projects created by creator, 4- IsFBConnected, 5- goal, 6- duration, 7- no. of images, 8- no. of characters in the project description, 9- no. of pledge tiers, 10- HasVideo, 11- HasYoutubeVideo, 12- ViewCountYouTubeVideo, 13- no. of tweets.	M1- variable 1 to 13 utilizing support vector machine(SVM) to predict project success.	Dynamic/ Kickstarter
Desai, Gupta, and Truong 2015 [69]	**Text data:** 1- project description, 2- risk and challenges description, **Meta data:** 3- goal, 4- category, 5- no. of videos, 6- no. of images, 7- no. of comments, 8- no. of projects previously created by creators, 9- no. of projects previously backed by creators, 10- no. of pledge levels.	**Text analysis:** 1- build TF-IDF matrices of uni, bi, and tri-grams from variable 1 and 2. 2- filter category related phrases, 3- use LIWC and word count to extract psycholinguistic categories from text. **Semantic analysis:** utilizing Stanford CoreNLP to assign scores (0,..,4) to comments. Where 0 represents most negetive and 4 represents most positive. **Success prediction:** utilize realized logistics regression to analyze the significance of variables. M1- metadata plus LIWC categories utilizing naive bayes. M2- metadata plus LIWC categories utilizing decision tree. M3 - metadata plus LIWC categories utilizing logistic regression. M4- metadata plus LIWC categories utilizing support vector mechine (SVM).	Static/ Kickstarter
Koch and Siering 2015 [70]	**Project specific aspects: (media richness)** 1- no. of words in project description, 2- no. of words in risk description, 3- HasImage/video, 4- no. of pictures, **(others)** 5- HasUpdates, 6- goal, **Founder specific aspects:** 7- no. of previously created projects by creators, 8- no. of previously backed projects by creators, **Controls:** 9- duration, 10- no. of Facebook friends, 11- category	M1- using all variables and utilizing logistic regression to predict project success.	Static/ Kickstarter
Rakesh, Choo, and Reddy 2015 [25]	**Project-based traits: (static features — generic)** 1- duration, 2- goal, 3- category, 4- sub-category, 5- location, 6- currency, 7- no. of rewards, **(static features — content-based)** 8- no. of words in project description, 9- no. of words in risk description, 10- no. of FAQs, 11- no. of images, 12- HasVideo, **(temporal features)** 13- accumulated pledged funds, 14- accumulated no. of backers, 15- no. of tweet promotions. **Personal traits: (creator personality)** 16- no. of projects previously created, 17- no. of projects backed, 18- success ratio of creator (p(success-curr|success-past)), **(backer personality)** 19- no. of backing, 20- categories of backed projects, 21- topical preference (conditional probability of user interest in category), 22- creator preference (conditional probability of user interest in creator), **Location-based traits:** 23- influence score of location (percentage of backers with same geo-location as project's), **Network-based traits: (project social)** 24- no. of promoters, 25- the tie strength, 26- the bi-connected components, 27- Page Ranke of promoters, **(backer social)** 28- the influence score of community over backer.	M1 - using all variables and utilizing gradient boosting decision tree (GBtree) to predict project success over first three days of campaign.	Dynamic/ Kickstarter
Robertson and Wooster 2015 [71]	1- goal, 2- duration, 3- first day pledged money, 4- no. of backers, 5- no. of first day backers, 6- no. of first day comments, 7- no. of created projects, 8- no. of backed projects, 8- HasVideo, 9- no. of updates, 10- no. of FB friends, 11- no. of first day FB shares, 12- category	M1- using all variables and utilizing regression model to predict the project's pledged money. M2- using all variables and utilizing regression model to predict the percentage of goal raised. M3- using all variables and utilizing probit specification to predict the project's success.	Static/ kickstarter
Hobbs, Grigore, and Molesworth 2016 [72]	**Network Management:** 1- no. of backers, 2- project's search result, 3- no. of FB shares, 4- pledged money, **Campaign Management: (pitch quality)** 5- pitch videos, 6- evidence of content precedence, 7- detailed text description, 8- impressions of quality, **(reward quality)** 9- reward overview, 10- content precedence in rewards, 11- value for money, 12- geographic vulnerability, 13- updates	Descriptive and comparative analysis	Static/ Kickstarter

Citation	Determinants	Model and Methodology	State & Platform
An, Quercia, and Crowcroft 2014 [73]	1- no. of updates, 2- no. of comments, 3- reward level, 4- website, 5- goal, 6- geographic dispersion, 7- growth rate, 8- backer tweets, 9- project description.	To predict the kind of backers (frequent or occasional) will back the project: M1- correlation between variable 1 to 4 with no of frequent backers, M2- correlation between high goal and no. of frequent backers, M3- correlation between geographical dispersion and no. of occasional backers, M4- correlation between growth rate and no. of frequent backers, M5- utilize Latent Drichilet Allocation (LDA) to analyze the similarity between tweets and project description to understand frequent backers tendency toward backing projects close to their topical interest.	Static/ Kickstarter
S.-Y. Chen et al. 2015[24]	**Intrinsic characteristics:** 1- category, 2- no. of FB friend, 3- no. of projects backed by creators, 4- no. of projects created by creators, 5- currency, **Financial Mechanism:** 6- goal, 7- no. of rewards, 8- maximum pledge, 9- minimum pledge, 10- average pledge, 11- STD of pledge, **Content Quality and Sentiment:** 12- no. of photos, 13- no. of videos, 14- no. of words, 15- no. of spelling error, 16- Flesch-Kincaid grade level, 17- sentiment score of description, **Social Interaction:** 18- no. of social words, 19- FBConnected, 20- no. of updates, 21- no. of comments, 22- no. of FB shares, 23- no. of FAQs, **Progression Effect:** 24- completeness (percentage of goal raised over time) 25- pledged money	M1- variable 1 to 23 & 25 utilizing random forest to predict project's success. M2- variable 1 to 24 utilizing random forest to predict project's success.	Static & Dynamic/ Kickstarter
Li, Rakesh, and Reddy 2016 [74]	**Project-based Features:** 1- duration, 2- goal, 3- no. of images, 4- HasVideo, 5- no. of comments, 6- no. of words in project description, 7- no. of words in risk, 8- no. of words in FAQs, 8- category, 9- geo-location, **Creators-based Features:** 10- no. of projects created by v=creators, 11- no. of projects backed by creators, 12- success ratio of the creator, 13- creator's FB profile features, **Social network features:** 14- tie-strength, 15- no. of bi-connected components, 16- PageRank scores of twitter of promoters, **Temporal Features:** 17- accumulated no. of backers over first three days, 18- accumulated pledged money over first three days, 19- no. of twitter promotions over first three days, 20- no. of FB shares.	Variables: Static: project-based and creators features, Social: social network features, 3days: temporal features Samples: 1- without failed projects, 2- with failed projects, M1/1&2- static utilizing censored regression with logistic distribution and log-logistic distribution, Cox proportional hazardous model, tobit regression, Buckley-James estimations, Boosting concordance index with sample 1 and 2. M2/1&2- static + social utilizing logistic distribution and log-logistic distribution, Cox model, tobit regression, Buckley-James estimations, BoostCI with sample 1 & 2. M3/1&2- static + 3days utilizing logistic distribution and log-logistic distribution, Cox model, tobit regression, Buckley-James estimations, BoostCI with sample 1 & 2. M4/1&2- static + social + 3days utilizing logistic distribution and log-logistic distribution, Cox model, tobit regression, Buckley-James estimations, BoostCI with sample 1 & 2.	Static & Dynamic/ Kickstarter
Moutinho and Leite 2013 [75]	1- no. of backers, 2- no. of comments, 3- no. of updates, 4- no. of levels of rewards, 5- no. of projects backed by creators, 6- category	Phase 1- predict the financing rate utilizing regression and all variables. Phase 2- choose 6 projects from kick starter and run survey to understand the appealing facts of these projects.	Static/ Kickstarter
Briggman 2014 [23]	1- goal, 2- pledged money, 3- funded percentage, 4- no. of backers, 5- no. of level of rewards, 6- no. of updates, 7- no. of comments, 8- duration	Predict the project's success using all variables and regression analysis for each category.	Static/ Kickstarter
Aleyasen 2014 [76]	Project description text	1- Build n-gram matrix using Lucene search engine 2- use K nearest or KNN classifier to predict the project's success. M1- training 3-grams, testing 3-grams M2- training 4-grams, testing 3 & 4-grams M3- training 4-grams, testing 4-grams M4- training 5-grams, testing 4 & 5-grams	Static/ Kickstarter
Kamath and Kamat 2016 [77]	1- category, 2- funded, 3- no of backers, 4- pledged money, 5- goal, 6- duration. 7- no. of updates, 8- HasVideo, 9- no. of rewards.	Predicts the following buckets (0 funded, less funded, partial, successful, above goal) with following model: M1- all variables utilizing naive bayes M2- all variables utilizing neural network M3- all variables utilizing random forest M4- all variables utilizing decision tree	Static/ Kickstarter
Lichtig 2015 [78]	1- duration, 2- no. of projects created by creators, 3- no. of projects backed by creators, 4- goal	Using all variables and utilizing empirical bayes model with negative binomial distribution to predict the number of backers	Static/ Kickstarter
Štofa and Zoričak 2016 [79]	1- campaign timing, 2- goal, 3- category relative size	All variables using logistic regression to study the effect of each variable on success of campaign	Static/ Kickstarter

Citation	Determinants	Model and Methodology	State & Platform
Dey et al. 2017 [22]	1- Project's Video, **Static features:** 2- goal, 3- no. of tweets, 4- no. of FB shares, 5- no. of reward levels, 6- no. of comments, 7- duration, 8- no. of images.	Step1- conducting survey on Amazon Turk to evaluate campaign videos. evaluating against following factors: 1- central cues or product-related factors: relevance, complexity, involvement, purchase intent, 2- peripheral cues or video-related factors: perception of video duration, video and audio quality, attitude toward the video. Step 2- predict the success of campaign for technology, fashion & design category. M1/1,2&3- static features utilizing logistic regression. M2/1,2&3- static features and product-related factors utilizing logistic regression. M3/1,2&3- static features and video-related factors utilizing logistic regression.	Static/ Kickstarter
Cordova, Dolci, and Gianfrate 2015 [80]	1- log(goal), 2- no. of backers, 3- log(mean of pledged money), 4- duration, 5- daily log(mean of pledged money), 6- IsLunchedInUSA, 7- IsLunchedInEurope, 8- no. of updates, 9- no. of comments, 10- TypeofFinancing	M1- all variables utilizing probit regression to predict technology project success. M2- all variables utilizing robust linear regression to predict technology project success.	Static&semi-dynamic/ Kickstarter, Indiegogo, Ulule, Eppela
Skirnevskiy, Bendig, and Brettel 2017 [81]	**Major characteristic of campaign:** 1- goal, 2- staff pick, 3- additional websites, 4- OriginUSA, **Project creator-related features:** 5- no. of previously created projects, 6- Average FB shares, 7- no. of FB friends, **Longitudinal aspect of campaign:** 8- early backers, 9- early fund raised, **Survey variables:** 10- no. of loyal backers self-reported, 11- no. of similar projects on other platforms, 12- social composition of backers in the early period, 13- social composition of backers in the remaining period.	M1- descriptive analysis using variables 12 & 13. M2- variable 1 to 11 utilizing logit regression to predict success of project. M3- variable 1 to 11 utilizing tobit regression to predict success of project.	Static & semi-dynamic/ Kickstarter
Sawhney, Tran, and Tuason, n.d. [82]	1- title, 2- summary, 3- description, 4- goal, 5- duration	Step 1- build unigrams matrix using title and summary of projects. Step 2- using deep learning techniques to analyze the sentiment of the description. Step 3- using part of speech tagging to understand the structure of sentences. Step 4- calculating the readability of description using Flesh-Kincaid test. Step 4- using the Latent Dirichlet Allocation to assign common topics to each projects' description. Step 5- overlap between the title and summary words and the words in the top ten identified topics as features. Step 6- establish unigrams and naive bayes as baseline to predict projects' success. Step 7- using unigrams, sentiments ,sentence structure, features, goal, and duration along with SVM to predict the success of project.	Static/ Kickstarter
Kaminski et al. 2017 [2]	1- video text, 2- survey results	Step 1- conducting survey on campaign, campaigner, and product characteristics to categorize the projects as lead projects and non-lead projects. Step 2- build unigrams matrices from video text and utilize penalize logistic regression to predict lead and non lead projects.	Static/ Kickstarter

Appendix B - Kickstarter scraping code

```
# coding: utf-8
from selenium import webdriver
import pandas as pd
import time
from datetime import datetime
from collections import OrderedDict
import re

chrome_path = r"D:\Course Log\ETM\Kickstarter\chromedriver_win32\chromedriver.exe"
browser = webdriver.Chrome(chrome_path)
browser.get('https://www.kickstarter.com/discover?ref=nav')
categories = browser.find_elements_by_class_name('category-container')

category_links = []
for category_link in categories:
    #Each item in the list is a tuple of the category's name and its link.
    category_links.append((str(category_link.find_element_by_class_name('h3').text),
                    category_link.find_element_by_class_name('bg-white').get_attribute('href')))


scraped_data = []
now = datetime.now()
counter = 1

for category in category_links:
    browser.get(category[1])
    browser.find_element_by_class_name('sentence-open').click()
    time.sleep(2)
    browser.find_element_by_id('category_filter').click()
    time.sleep(2)

    for i in range(27):
        try:
            time.sleep(2)
            browser.find_element_by_id('category_'+str(i)).click()
            time.sleep(2)
        except:
            pass

   #while True:
   #  try:
   #     browser.find_element_by_class_name('load_more').click()
   #  except:
   #     break

    projects = []
    for project_link in browser.find_elements_by_class_name('project-title'):
```

```
        projects.append(project_link.find_element_by_tag_name('a').get_attribute('href'))

    for project in projects:
        time.sleep(2)
        print(str(counter)+': '+project+'\nStatus: Started.')
        project_dict = OrderedDict()
        project_dict['Category'] = category[0]
        browser.get(project)
        project_dict['Name'] = browser.find_elements_by_class_name('green-dark')[0].text

        try:
            try:
                project_dict['Num_Of_Backers'] =
int(browser.find_element_by_id('backers_count').text.replace(',',''))
            except:
                project_dict['Num_Of_Backers'] = int(browser.find_element_by_class_name('num
h1 bold').get_attribute('data-backers-count'))
        except:
            project_dict['Num_Of_Backers'] =
int(browser.find_element_by_class_name('NS_projects__spotlight_stats').find_element_by_tag_
name('b').text.replace(',','').split(' ')[0])

        try:
            project_dict['Currency'] = str(browser.find_element_by_id('pledged').text[0])
        except:
            project_dict['Currency'] =
str(re.sub(',','',browser.find_element_by_class_name('money').text[0]))

        try:
            project_dict['Amount-Pledged'] =
float(browser.find_element_by_id('pledged').text[1:].replace(',',''))
        except:
            project_dict['Amount-Pledged'] = float(browser.find_elements_by_class_name('mb1')[-
1].text[1:].replace(',',''))

        try:
            project_dict['Goal'] =
float(browser.find_elements_by_class_name('money')[1].text[1:].replace(',',''))
        except:
            project_dict['Goal'] =
float(browser.find_elements_by_class_name('h5')[8].find_element_by_class_name('money').text
[1:].replace(',',''))

        project_dict['Funded'] = int(project_dict['Amount-Pledged'] >= project_dict['Goal'])

        try:
            project_dict['Time_Remaining'] =
(browser.find_element_by_class_name('ksr_page_timer').find_element_by_class_name('num').t
ext,
```

```
browser.find_element_by_class_name('ksr_page_timer').find_element_by_class_name('text').tex
t.split(' ')[0])
        except:
            project_dict['Time_Remaining'] = 0

        project_dict['About'] = '\n'.join([a.text for a in
browser.find_elements_by_tag_name('p')[5:-3]])

        project_dict['Num_Of_Comments'] =
re.search('\d+',browser.find_elements_by_class_name('js-load-project-content')[3].text).group()
        project_dict['Num_Of_Updates'] =
re.search('\d+',browser.find_elements_by_class_name('js-load-project-content')[2].text).group()

        print('Status: Done.')
        counter+=1
        scraped_data.append(project_dict)

later = datetime.now()
diff = later - now

print('The scraping took '+str(round(diff.seconds/60.0,2))+' minutes, and scraped
'+str(len(scraped_data))+' projects.')

df = pd.DataFrame(scraped_data)
df.to_csv('kickstarter-data.csv')
```

Appendix C - Checking the sutiability of dependency relations for detecting product fetatures

As explained in section 3.1.2.2, syntactic relations extraction rules based on syntactic dependencies are selected to extract product features in the double propagation process. Qiu et al. [29] employed direct syntactic relations, including *mod*, *pnmod*, *subj*, *s*, *obj*, *obj2*, and *conj* to identify opinion features (aspects) of products.

UDPipe r package is used to parse dependency relations. However, *UDPipe* uses universal dependency grammar, while Qiu et al. are used dependency relations in MiniPar. Because of the vast diffusion of the universal dependency grammar in natural language programming, the dependencies considered by Qiu et al. [29] are matched with universal dependency relations as illustrated in Table 46. The matching process is similar to Kang and Zhou [28] approach with some modifications. In Table 46 rows correspond with functional categories in relation to the head, and columns correspond to structural categories of the dependent. All the relations mentioned in Table 46, as well as conj are considered for subjective features extraction rules.

	Nominals	**Clauses**	**Modifier Words**
Core arguments	*nsubj* *obj* *iobj*	*csubj* *ccomp* *xcomp*	
Nominal dependents	*nmod* *appos*	acl	*amod*
Coordination	*MWE*		
conj	*compound*		

Table 46- Universal dependency relations

The next step is to examine the suitability of each dependency relation. Also, examine the possibility of more pruned results by modifying the rules. Followings are the number of relations for each type of direct relations considered in rule 1 and 3 in double propagation: *obj* 28 relations, *nsubj* 981 relations, *iobj* 0 relations, *nmod* 86 relations, *appos* 23 relations, *csubj* 1 relations, *ccomp* 1 relations, *xcomp* 0 relations, *acl* 45 relations, and amod 18574 relations. *Amod* relations are the most prevailed ones. Figure 36 and Figure 37 show the example of *amod* relations. Dependency graphs are displayed using the *python spacy* package, so there is a small discrepancy between the actual dependency grammar used with the ones displayed here.

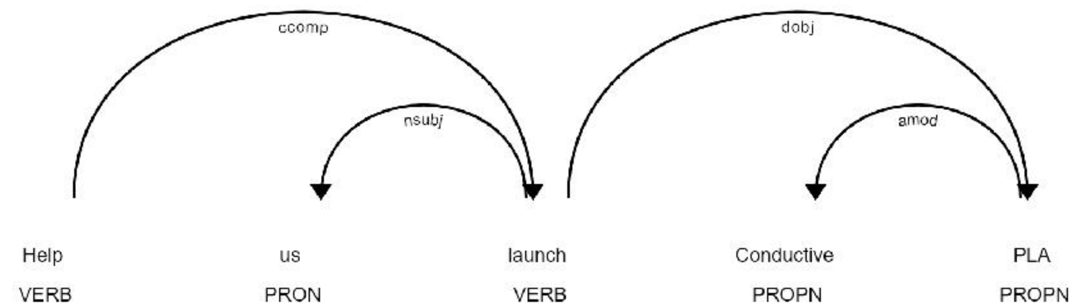

Figure 36 - Dependency relations for "Help us launch Conductive PLA and you will be able to!"

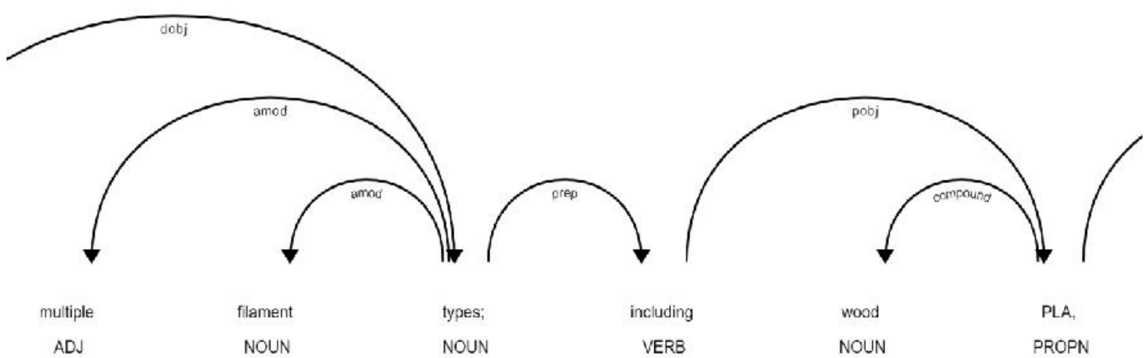

Figure 37 - Dependency relations for "B-Creative Printer accepts multiple filament types; including wood PLA, which allows the users to create items that have a very lovely wood appearance."

There is another dependency that hasn't been included in the double propagation initially. As displayed in Figure 38, compound is a dependency relation that capable of capturing product features. The compound is a relation for multiword expressions (MWE) like noun compounds. Though it seems double propagation finds the nouns and adjectives have compound dependency without considering the relation, the relation added to a list of rules for comprehensiveness.

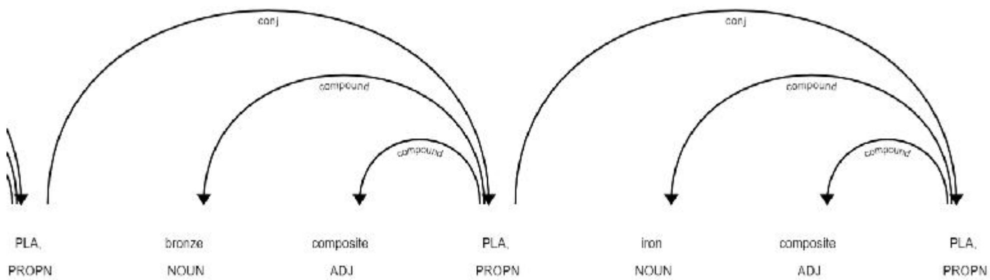

Figure 38 - Partial dependency relations for "Pingo can print with PLA, PHA, PETG, TPU, TPE, wood composite PLA, bronze composite PLA, iron composite PLA, UV color changing filament, PET, and much more."

For pruning purposes, the noise like “team members” shows the same dependency pattern as the most dominant relation for product features amod and compound shown in Figure 39. So, the noises can’t be eliminated by refining the dependency rules. With the rules such as obj, iobj, xcomp, and ccomp, there aren’t enough instances to make difference in pruning noises.

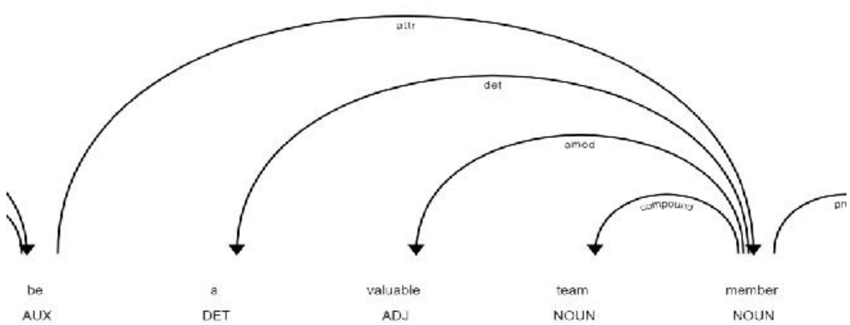

Figure 39 - Dependency relations for "He will continue to be a valuable team member in the R & D"

Appendix D - Evaluating the performance of double propagation in eleminating noise in the candidate pool of product features

A network of highly frequent co-occurred nouns and adjectives is generated to check the goodness of noise reduction of the double propagation approach. *Gephi* software has been used to draw the graph based on the co-occurrence of nouns and adjectives. Figure 40 illustrates a network of co-occurrence nouns and adjectives with a frequency higher than 6. The frequency is restricted to keep the graph legible.

The phrases such as “market today,” “near future,” “global solution,” or universal terms on Kickstarter platform such as “team member,” “early bird,” “Kickstarter campaign” are considered as noise. Some of these noises, such as the “Kickstarter campaign,” “global solution,” and so on, are filtered by using a double propagation approach. However, there are other noises such as “early bird” and “team member” that ended up in the extracted product features. So, the rule-based approach eliminates the noises to some degree in this context.

The result of the rule-based approach is also influenced by defining accurate rules. Refining the extraction rules is discussed further in Appendix C. Rule refinement is attempted for three purposes:

- Matching the universal dependency relations with the rules used by Qui et al. [29].
- Check the comprehensiveness of chosen rules.
- Changing rules to have more refined results.

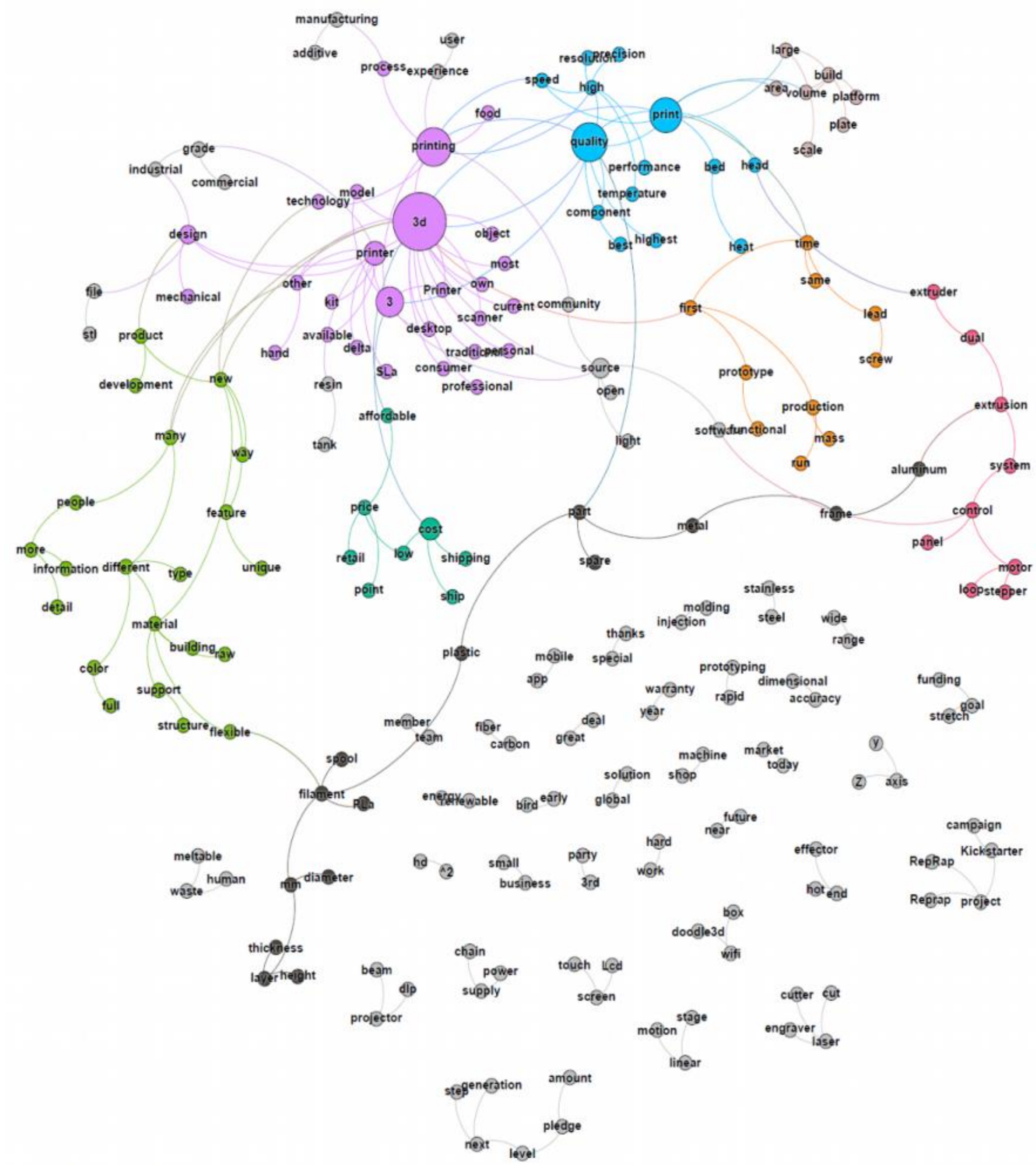

Figure 40- Co-occurrence graph of nouns and adjectives with a frequency higher than 6.

Another way of improving results is by using lexico-syntactic patterns along with dependency relations. For the approaches such as part-whole rules that rely on lexico-syntactic association, regular expressions can be used to extract the objective rules. These rules serve as complementary rules to provide a more comprehensive result. The lexico-syntactic relation is suitable to capture the product features that are conveyed in a comparative format [28].

The shiny app[6] is built to test the usefulness of adding part-whole relations. The app identifies the phrase and returns the sentences that contain the given phrase. NP_x has NP_y is one of the considered rules in part-whole relations. For instance, “printer has” expression follows the same pattern, and Figure 41 shows some of the sentences that contain. The inspection, here, shows that creator’s opinion toward product feature of 3d printer like “printer has very short learning curve” phrase—which is not the goal here—follow NP_x has NP_y pattern. Also, it seems the double propagation result covers this pattern as well. For example, “color blending technology” —NP_y— is already in among extracted noun phrases.

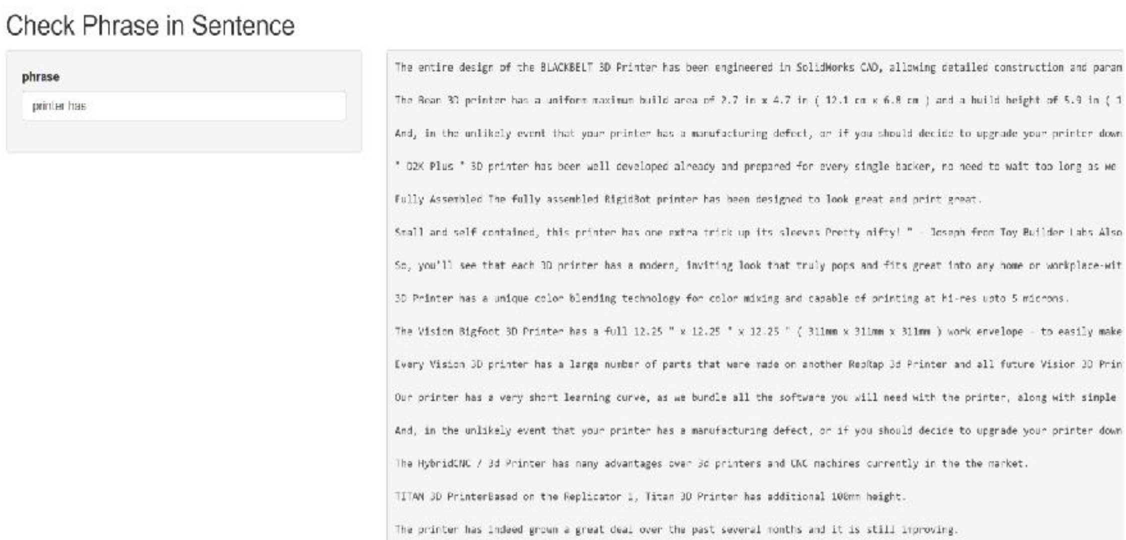

Figure 41 - Some of the sentences that contain "printer has" expression.

A similar conclusion can be drawn for other patterns of whole-part relations. For instance, NP_x of NP_y pattern is about the type, generation, or cost of the printer rather

[6] https://ninach.shinyapps.io/phrase_checker/

than product features. Checking other patterns showed that using whole-part relations has no added value here. For this reason, the whole-part patterns aren't included in the extraction process.

Appendix E - Noun phrases associated with each product feature categories

Multiple Filament Extruder	
dual extruder	*dual extruder model*
dual extrusion	*multiple extruders*
dual extruders	*independent extruders*
dual extrusion upgrade	*interchangeable extrusion heads*
second extruder	*separate extruders*
double extrusion	*multiple color extruder*
dual extruder system	*triple extrusion*
multiple extrusions	*dual plastic extruders*
dual extrusion component	*dual extrusion capabilities*
dual extruder systems	*dual use extruder*
interchangeable extruder head	*optional dual extruder*
dual extrusion hotend	*dual extrusions*
dual extruder option	*double extruder*
dual extrusion upgrades	*double extruder module*
dual extruders upgrade	*triple extruder*
triple extruder upgrade	*multi-extruder option*
exchangeable extruders	*dual extruder options*
second filament extruder	

Extruder type and quality	
dedicated tungsten extruder	*peristaltic pump extrusion*
tungsten extruder	*pump extrusion*
clay extruder	*pump extrusion system*
anodized aluminum extrusion	*wasp clay extruder*
controllable peristaltic pump extrusion	*titan extruder*

Nozzle Size	
nozzle diameter	*mm nozzle*
nozzle size	*mm diameter nozzle*
larger nozzle	*smaller nozzle diameter*

diameter nozzle	*larger diameter nozzle*
smaller nozzle	*tiny nozzle*
interchangeable nozzle diameters	*nozzle diameters*
large diameter nozzles	*diameter nozzles*
smaller nozzles	*Small nozzle*

Filament Size	
filament size	*mm diameter filament*
filament diameter	*mm filaments*
micro filament	*mm diameter filaments*
diameter filament	*diameter filaments*
industry filament size	

Nozzle Type and Quality	
stainless steel nozzles	*high melt nozzle*
steel nozzles	*low temp nozzle*
alloy nozzle	*high temp nozzle*
quick change nozzles	*high wear nozzles*
glass nozzle	*wear nozzles*
titanium alloy nozzle	*hot nozzles*
interchangeable nozzles	*replaceable nozzles*
low melt nozzle	*custom stainless steel nozzles*
brass nozzle	*diamond nozzle*
interchangeable nozzle	*nozzle hardness*

Non-Composite Thermoplastic Filament Type	
plastic filament	*compatible filament pla*
pla filament	*pva filaments*
3d plastic filament	*semi-flexible filaments*
filament abs	*soluble filament*
mm pla filament	*3d plastic filament prices*
conductive pla filament	*plastic filament prices*
abs filaments	*experimental plastic filaments*
filament pla	*conductive abs filament*
plastic filaments	*mm plastic filament*
abs filament	*3d plastic filament deposition*
low temperature filament	*plastic filament deposition*
3d pen filament	*sample pla filament*
pen filament	*pla filament pack*
pla plastic filament	*quality pla filament*
flex filament	*same pla filament*

polycarbonate filament	*temperature 3d filament*
low melt filaments	*abs pla*
lower melt filaments	*conductive pla*
pla filament	*normal pla*
mm pla	*translucent red pla*
pla plastic	*red pla*
pla pla	*conductive pla filament*
printer pla	*filament pla*
pla materials	*kg spool pla*
pla spool	*spool pla*
other pla	*plastic extruder*
flexible pla	*thermoplastic materials*
pla plastics	*biodegradable pla*
pla material	*natural pla*
plastic filaments	*common plastic*
plastic problem	*quality pla*
pla fdm	*easier pla*
pla plastic filament	*pla printer*
white pla	*affordable pla*
nontoxic pla	*pla cmykw*
pla cmykw color	*plastic colors*
colorfabb pla color	*complex plastic*
3d printing plastic	*spool pla material*
printing plastic	*economy pla*
compatible filament pla	*standard pla*
edition pla	*standard pla formula*
extra pla	*pla formula*
various plastics	*useful 3d plastic*
3d pla	*3d plastic*
preferred plastic material	*pla pieces*
3d printing pla	*plastic material layer*
pla combination	*mm pla cartridges*
print pla	*pla cartridges*
type plastic	*hard plastics*
biodegradable pla plastic	*mm plastic*
friendly pla	*mm plastic filament*
plastic pieces	*pla perimeters*
plastic prints	*plastic elements*
lbs pla	*abs plastics*
3d plastic filament prices	*pla printer3d*
plastic filament prices	*pla printer3d printers*
experimental plastic filaments	*hot end pla*
plastic residue	*end pla*
non-plastic parts	*durable plastic*
pva plastic	*one pla*
printing abs pla	*typical plastic deposition*

typical plastic deposition system	*ground plastic*
plastic deposition system	*raw pla*
3d plastic filament deposition	*raw pla alternative*
plastic filament deposition	*pla alternative*
sample pla filament	*large pla*
pla filament pack	*large pla printing*
popular thermoplastics	*pla printing*
high quality pla	*thermoplastic 3d printing*
quality pla filament	*quality pla prints*
pla fdm plastic	*resistant plastic*
fdm plastic	*robust plastic printing*
robust plastic printing capabilities	*abs upgrade*
plastic printing	*abs filaments*
plastic printing capabilities	*polycarbonate abs*
same pla	*abs material*
same pla filament	*natural abs*
printer plastic	*abs filament*
preferred plastic	*abs juice*
plastic component	*current abs*
plastic section	*starter abs*
temperature sensitive plastic.	*larger abs*
sensitive plastic.	*larger abs parts*
mm diameter pla	*standard abs*
diameter pla	*successful abs*
use pla	*successful abs printing*
abs support	*abs prints*
abs r	*abs part*
lb abs	*abs part intact*
printing abs	*lbs abs*
abs parts	*large abs*
abs printing	*abs spools*
filament abs	*abs resin*
abs odours	*conductive abs filament*
flat abs	*abs particles*
multi-color abs	*abs plastics*
full abs	*abs heat*
full abs support	*abs heat bed*
support abs	*color abs*
gray abs	*taulman nylon*
printing abs pla	*harder nylon*
conductive abs	*nylon prints*
nylon copolymer	*plastic extruders*
plastic extruder	*integrated flexible material extrusion*

Composite Thermoplastic Filament Type	
composite filaments	*carbon fiber pla*
carbon fiber filament	*fiber pla*
fiber filament	*woodlike pla*
specialty composite filaments	*carbon pla*
carbon fiber filaments	*wood composite pla*
fiber filaments	*bronze composite pla*
stainless steel filament	*iron composite pla*
steel filament	*ordinary clay*
available conductive filaments	*desktop clay*
conductive filaments	*desktop clay 3d*
tech composite filaments	*clay 3d*
many composite filaments	*clay 3d printer*
new composite filaments	*clay model*
bamboo filaments	*clay printing*
abrasive composite filaments	*clay printer*
wood filament	*friendly desktop clay*
wood pla	*loading clay*
composite pla	*different clays*
ordinary clay material	*best desktop clay*
clay material	*other clay*
clay performance	*3d printing clay*
clay pressure	*printing clay*
recyclable ordinary clay	*clay extruder*
3d clay	*3d clay printer*
load clay	*clay type*
clay type materials	*modeling clay*
wasp clay	*wasp clay extruder*
precious metal clays	*metal clays*
wood pla	*wood filler*
woodlike pla	*wood filament*
wood composite	*wood composite pla*
high tech composite	*tech composite*
composite bearings	*other composite*
carbon fiber composite	*fiber composite*
composite materials	*composite linear*
composite linear motion	*tech composite bearings*
composite frame	*composite carbon fiber*
composite frame parts	*composite matrix*
specialty composite	*many other composite*
interesting composites	*many other composite microfibers*
composite carbon	*other composite microfibers*
composite microfibers	*aluminum extrusions*
aluminum extrusion	*metal extruder*
flexible material extrusion	*ceramics extruder*
composite extruder	

Food Paste intake	
paste extruder	*dual paste extruders*
discov3ry paste extruder	*paste extruders*
affordable paste extruder	*2nd paste extruder*
universal paste extruder	*paste extrusion*
paste extrusions	*paste extrusion module*
food extrusion	

HotEnd Extruder	
hot end extruder	*hot end*
hot ends	*other hot end*
diamond hotend	*hot end nozzles*
extruder hotend	*hotend moves*
separate hot ends	*hot end upgrade*
head hotend	*metal hexagon hotend*
new hot end	*hot end assembly*
e3d hotends	*simple hotend*
hexagon hotend	*dual extrusion hotend*
e3d v6 hotend	*extrusion hotend*
v6 hotend	*finest hotends*
hot end nozzle	*other hotend*
e3d hotend	*premium hotend*
hotend combo	*premium e3d hotends*
own hot ends	*maximum hot end*
hot end temp	*maximum hot end temperature*
hot ends temperature	*hot end temperature*
material hot end	*hot end design*
hotend assembly	*online metal hotend*
hot endreprap	*dual hot ends*
hot endthanks	*single hot end*
hot end c	*hot end pla*
separate hot end	*second hotend*
simple hot end	*authentic e3d hotend*
quality e3d hotends	*adjustable hotends*
3d online metal hotend	*dual hotend*
metal e3d hotend	*genuine e3d hotends*
accurate hot end	*genuine diamond hotend*
hot end combine	*hotend mounting*
e3d volcano hotend	*available hotends*
volcano hotend	*heat sinks*
optimizing heat	*optimizing heat vents*
heat vents	*simple heatsink*

heat flux	*heat flux results*
powerful heaters	*heater cartridge*
heating element	*hot end nozzle*
hot end nozzles	

Visual Properties of Materials	
floreon filament	*color filaments*
color filament	*colour filament*
cmykw color filament	*color filament spools*
dark filaments	*basic color filaments*
red ninjaflex filament	*different color filaments*
translucent red pla	*red pla*

Nozzle Cooling System	
liquid cooling	*liquid cooling block*
cooling fan	*cooling block*
blower fan	*additional cooling*
cooling fans	*integrated blower fan*
cooling system	*cooling fan noise*
print cooling	*print cooling fan*
extra fan	*common axial fans*
liquid cooling system	*axial fans*
air cooling	*powerful blower fan*
print layer cooling	*second blower fan*
layer cooling	*integrated cooling*
layer cooling fan	*strong fan*
fan noise	*optimal cooling*
uneven cooling	*fan system*
big fans	*efficient cooling*
fan cooling	*efficient cooling fans*
uses air cooling	*cooling process*
automatic print layer cooling	*direct cooling*
air cooling system	*controllable centrifugal fan*
centrifugal fan	*extruder cooling*
extruder cooling fan	*coolant system*

Bowden Extruder Type	
bowden extruders	*bowden extrusion system*
bowden style extruder	*bowden extruder*
bowden design extruder	*bowden extruder set*
bowden extrusion	

Dissolvable Material	
dissolvable support	*dissolvable parts*
dissolvable support material	*dissolvable support materials*
dissolvable hips	*dissolved plastic*
dissolvable hips filament	

Color Printing	
full color	*dual colour printing*
different colors	*color blending*
multiple colors	*color filaments*
colour range	*different color*
color mixing	*color process*
color scheme	*color mix*
color printing	*multi-color 3d printer*
custom colors	*color change*
color 3d printer	*color sample pla*
color filament	*color print*
dual colour	*full color 3d*
colour printing	*custom color*
color printer	*color models*
multi-color printing	*full color model*
pla color	*color model*
color capacity	*colorfabb pla*
new color	*color version*
different colours	*color prints*
dual color	*colors print*
colour filament	*favourite colours*
unique color	*full color blender*
colorful prints	*color blender*
full color capacity	*affordable full color*
color contrast	*affordable full color 3d*
multi-color prints	*print unlimited colors*
full color process	*unlimited colors*
multi-color models	*print color*
plastic colors	*different custom color*
colorfabb pla color	*multi-colored part*
multiple color	*color nozzle*
multiple color extruder	*color 3d prints*
color extruder	*full color nozzles*
color extruder head	*color nozzles*
acrylic color	*full cmykw color*
integrated color	*pla cmykw color*

dual colour prints	*cmykw color filament*
colour prints	*color filament spools*
easy color mixing	*color selection*
unique color blending	*multi-color abs*
color blending technology	*color printer prototype*
unique tri-color	*dual color printing*
colour extruder upgrade	*color printing head*
multicolor 3d printer	*3d color printer.*
3d4c full colors	*color printer.*
3d color printer	*color printing3d*
full color printer	*real full color*
accurate color blending	*colored 3d*
cheapest color 3d	*detailed color*
color printers	*detailed color contrast*
multi-color diamond nozzle	*colour extruder*
color abs	*printing colors*
colorful material	*different color filaments*
full color desktop	*infinite color possibilities*
color desktop	*color possibilities*
color desktop 3d	*various colors*
color process desktop	

Auto Z Height	
auto nozzle height	*nozzle height control*

Auto Leveling System	
auto bed leveling	*autobed leveling*
auto leveling	*auto calibration*
self leveling	*auto calibration routine*
automatic bed leveling	*faster autocalibration*
automatic leveling	*automatic calibration*
bed leveling sensor	*automatic calibration probe*
leveling sensor	*calibration probe*
automatic leveling sequence	*autonomous calibration*
auto levelling	*autonomous calibration system*
bed self leveling	*new automated calibration*
self leveling system	*new automated calibration function*
automated calibration	*calibration function*
automated calibration function	

Calibration and Leveling System	
point leveling	*total calibration stable*
point leveling system	*calibration stable*
limit switches	*fine calibration*
mechanical switches	*step calibration*
little calibration	*step calibration process*
calibration system	*calibration supplies*
bed calibration	*continuous recalibration*
calibration maintenance	*complex initial calibration*
calibration routine	*complex initial calibration process*
factory calibration	*initial calibration*
print bed calibration	*initial calibration process*
calibration process	*calibration switch*
calibration feedback	*calibration switch states*
calibration feedback loop	*calibration steps*
constant recalibration	*better software calibration*
final calibration	*software calibration*
mm calibration cube	*bed calibration system*
calibration cube	*axis calibration*
calibration cube steps	*calibration image*
calibration sensor	*calibration functions*
calibration simplicity	*smoothie board calibration*
finicky calibration	*board calibration*
calibration time	*delicate calibration*
total calibration	*calibration pattern*

Delta Motion System	
delta printer	*delta approach*
metal delta	*delta compatibility*
morpheus delta	*mini deltamaker*
delta printers	*delta style printer*
delta design	*multimaterial delta*
rappidelta jr	*material delta*
delta type	*material delta 3d*
3d delta	*new delta*
delta 3d	*new delta printer*
delta 3d printer	*delta concept*
true delta	*innovative delta*
delta platform	*innovative delta printer*
delta arms	*true delta operation*
delta robot	*delta type printers*
deltamaker team	*rigid 3d delta printer*
3d delta printer	*rigid delta*
delta mechanism	*rigid delta structure*

delta style	*delta structure*
true delta design	*regular delta*
delta printer kit	*entire delta platform*
linear delta	*scale delta platforms*
linear delta robot	*delta platforms*
delta robot platform	*high quality delta*
3d delta printers	*quality delta*
deltamaker prototype	*quality delta class*
superb delta	*delta class*
superb delta printer	*trium delta*
robust delta	*trium delta 3d*
robust delta printer	*top delta*
3d ceramic delta	*top delta printer*
mainstream delta printer	*high reliability.the rappidelta*
delta printer alternative	*reliability.the rappidelta*
deltaprintr design	*reliability.the rappidelta jr*
delta style 3d	*delta designs*
delta style printers	*delta type robots*
delta robots	*delta carriages*
delta towers	*first delta 3d*

Cartesian System	
cartesian system	*cartesian 3d printers*
cartesian gantry	*cartesian printer*
traditional cartesian 3d	*rappidelta design*
traditional cartesian 3d printers	*cartesian gear*
cartesian 3d	

Stepper Motor, Linear Bearings, Lead Screw, Belt	
stepper motors	*steel rods*
stepper motor	*timing pulleys*
loop motor	*ball bushing*
loop motor control	*ball head*
linear bearings	*motor control systems*
stepper drivers	*motor control ensures*
lead screw	*mm ballscrew*
lead screws	*motor control allows*
dc motors	*closed loop motor*
ball screw	*motor driver*
smooth rods	*bent drive screw*
linear motion components	*drive screw*
motion components	*special screws*
precision stepper	*motor design*

precision stepper motor	*motor mounts*
torque stepper	*full leadscrew*
ball bearings	*most extruder motors*
threaded rods	*extruder motors*
high torque stepper	*motor stalls*
dc motor control	*belt technology*
motor control system	*screwdriver bit*
stepper driver	*precision screwdriver*
timing belts	*precision screwdriver set*
industrial grade stepper	*screwdriver set*
grade stepper	*cheap bearings*
grade stepper motors	*stepper motor drivers*
motor drives	*more steppers*
pulley system	*premium stepper*
carbon rods	*premium stepper motors*
precision ball	*other linear motion*
precision ball screw	*axis motor couplers*
belt drives	*motor couplers*
nema motor	*standard motors*
high resolution stepper	*lighter motors*
resolution stepper	*motor technology*
resolution stepper motors	*industrial grade motors*
torque stepper motor	*grade motors*
grade leadscrews	*expensive stepper*
different screws	*expensive stepper motors*
motor drivers	*composite linear motion*
z motors	*linear motion bearings*
linear motion system	*motion bearings*
loose belts	*tech composite bearings*
axis motor	*adjustable bearing*
high performance motors	*adjustable bearing retainers*
performance motors	*bearing retainers*
extreme torque motors	*metal bearings*
torque motors	*custom polymer bearings*
other motor	*polymer bearings*
composite bearings	*motors cost*
ballscrew actuation	*typical motors*
triple pulley	*better bearings*
triple pulley system	*utilizing ballscrews*
push rods	*industrial ballscrews*
precise motion	*motion technology*
mm linear bearings	*micro motion*
linear rods	*micro motion chip*
acme lead screws	*motion chip*
lead screw design	*carbon fiber rods*
screw design	*fiber rods*

axis motors	*screw deflection*
acme screw	*high speed rail*
stepper motor drive	*speed rail*
motor drive	*speed rail system*
motor drive extrusion	*quality lead screws*
triaxial motion	*full size basketballs*
belt tensioner	*size basketballs*
linear actuation speed	*magnetic ball end*
leadscrew nut	*ball end rods*
torque stepper motors	*end rods*
screw system	*expensive belts*
linear guide rods	*traditional drive belts*
guide rods	*drive belts*
z motor	*high precision motion*
linear ball	*precision motion*
ball linear	*bulky motors*
high quality stepper	*screwless cube*
quality stepper	*screwless cube gears*
quality stepper motors	*motion controls*
belt drive	*precise motion control*
ultra-precision magnetic ball	*modular microstepping motor*
ultra-precision magnetic ball joints	*microstepping motor*
magnetic ball joints	*microstepping motor drivers*
upgraded ball	*mm ball bearing*
upgraded ball joints	*ball bearing*
ball studs	*mm linear rod*
stepper motors upgrade	*linear rod*
motors upgrade	*xl timing belt.*
deg stepper	*timing belt.*
deg stepper motors	*acme lead screw*
igus rod	*lead screw drive*
basket ball	*screw drive*
cheaper linear bearings	*precision linear motion*
grade ballnut	*spindle speed*
chinese ball	*axis linear motion*
high precision ball	*smooth rod*
ball screw linear	*axis lead screw*
screw linear	*y axis motors*
screw linear stage	*fine motor*
single stepping motor	*fine motor skills*
stepping motor	*motor skills*
linear ball bearings	*stepper motor control*
ball nose	*motor control structure*
ball nose bit	*plastic drive pulley*
extruder motor	*drive pulley*
novel belt	*plastic pulleys*

unique lead screw	*stronger linear motion*
screw design allows	*linear motion guides*
lead screw system	*precise lead screws*
stepper motor controllers	*typical belt*
motor controllers	*abec bearings*
different belt	*precision lead screws*
different belt pulleys	*precision lead screw*
belt pulleys	*leadscrew nut options*
industrial bearings	*quality linear motion*
tiny set screw	*large high torque stepper*
set screw	*motion control firmware*
traditionnal linear bearings	*potential operating speeds*
flat screwdriver	*visible screws*
head screwdriver	*ball screw system*
ceramic screwdriver	*z motor bracket*
precise dc motor	*motor bracket*
precise dc motor control	*best motors*
direct current encoder motors	*screw drivers*
current encoder motors	*powerful motors*
encoder motors	*costly belts*
special dc motor	*commercial linear ball*
motor control board	*stepper mount*
axis rod	*full ball*
servo motors	*ball linear slides*
hybrid stepper	*backlash ballscrews*
hybrid stepper motors	*blacklash ballscrews*
extra bearings	*blacklash ballscrews assemblies*
trapezoidal rods	*ballscrews assemblies*
large stepper	*smaller motors*
large stepper motors	*add ballast*
own motor	*precision acme screw*
own motor driver	*screw nut*
kysan stepper	*precision linear bearings*
kysan stepper motor	*integrated stepper drivers*
hot rod	*linear motion type*
double ball	*y belts*
double ball bearings	*precision acme screws*
point adjustment screws	*acme screws*
adjustment screws	*mm rod*
spherical bearings	*belts protonium*
general motors	*motion steppers*
belt tensioning	*delrin anti-backlash leadscrew*
anti-backlash lead screws	*delrin anti-backlash leadscrew nut*
motor system	*anti-backlash leadscrew*
motor shafts	*anti-backlash leadscrew nut*
traditional belt	*belt tension*

traditional belt design	*full leadscrew system*
belt design	*leadscrew system*
cm torque stepper	*filament rod machine*
axis screw	*rod machine*
area linear motion	*screw machine*
magnetic end rod	*same length screw*
end rod	*length screw*
linear rail motion	*powerful stepper*
screw fixture	*powerful stepper drive*
screw holes	*stepper drive*
der belt	*precise ball*
many motors	*precise ball screw*
durable ball	*motor mount*
durable ball bearings	*few motors*
high voltage motor	*torque motor*
voltage motor	*kevlar synchronous belts*
thick steel rod	*kevlar synchronous belts protonium*
steel rod	*synchronous belts*
belt drive printers	*synchronous belts protonium*
bouncy balls	*performance motor*

Wi-Fi	
usb wifi	*usb wifi dongle*

USB Port	
usb cable	*integrated usb*
usb port	*integrated usb hub*
usb stick	*usb hub*
usb flash	*usb ports*
speed usb	*usb drive*
usb connection	*usb cables*
usb printer	*high speed usb*

LCD Screen	
lcd screen	*lcd interface*
lcd panel	*lcd desktop*
lcd control	*lcd desktop 3d*
lcd display	*full graphic lcd*
lcd controller	*full graphic lcd screen*
lcd control panel	*graphic lcd*
large lcd	*graphic lcd screen*

high resolution lcd	*glcd graphic controller*
resolution lcd	*visible lcd screen*
flat screen	*computer screen*
lcd contact	*inch screen*
lcd contact exposure	*intuitive lcd*
inch touchscreen	*intuitive lcd display*
capacitive touch	*full lcd*
screen interfaces	*full lcd display*
lcd readout	*lcd control knobs*
screen display	*lcd control screen*
lcd 3d printing	*own lcd*
lcd 3d printer.	*own lcd display*
viki lcd	*screen lcd*
screen size	*lcd screen side*
new lcd	*upgraded lcd*
new lcd screen	*tablet screens*
ultra high resolution lcd	*lcd photo*
lcd screen upgrade	*lcd photomask*
lcd 3d printer	*oled screen*
lcd printers	*positioned lcd*
lcd uses	*positioned lcd controller*
lcd uses photo-polymerization	*large lcd screen*
resolution lcd screen	*high quality lcd*
lcd surround	*quality lcd*
screen device	*video screen*

Touch Screen	
touch screen	*touch laser*
touch button	*touch laser sla*
touch software	*high qualitytouchscreen lcd*
pegasus touch	*high qualitytouchscreen lcd desktop*
friendly touch	*qualitytouchscreen lcd*
friendly touch screen	*qualitytouchscreen lcd desktop*
touch sensors	*kickstarter touch*
device touch	*touch produces*
touch screens	*pc. pegasus touch*
updated touchscreen	*touch experience*
updated touchscreen interface	*future upgrades touch*
touchscreen interface	*upgrades touch*
touch screen interfaces	*upgrades touch control*
user friendly touch	*touch control*
full color touch	*touch control panel*
color touch screen	*capacitive touchscreen*
inch touch	*capacitive touchscreen allows*

inch touch screen	*touchscreen allows*
touch screen display	*device touch screen*
powerful touchscreen	*wireless full color touch*
intuitive touch	*wireless touch*
intuitive touch screen	*intuitive touchscreen*
ordinary touchscreen	*few touches*
final touches	*few touches formaker*
touch sensor	*touches formaker*
capacitive touch sensors	*color touch screens*
mobile device touch	*small touch*
device touch screens	*printerthe astrobox touch*
capacitive touch buttons	*astrobox touch benefits*
touch buttons	*touch benefits*
touch kickstarter	*touch benefits developers*
touch kickstarter trailer	*astrobox touch kickstarter*
pegasus touch laser	

Open Source Software	
open source software	*most open source software*
fantastic open source software	*standard open source software*
open source approach	*other open source software*
major open softwares	*source software configuration*
open softwares	*intuitive open source software*
source software platforms	*open software*
latest open source software	*open source softwares*
various open source softwares	*source softwares*
powerful open source software	

Software/UI	
printer software	*use software*
printing software	*uniz software*
control software	*software platform*
controller software	*dedicated printing software*
modeling software	*printing software toolchain*
design software	*software toolchain*
3d modeling software	*software package*
cad software	*painting software*
3d printing software	*software update*
software development	*software optimizations*
mobile app	*future software*
3d software	*future software updates*
3d printer software	*software specs*
mobile apps	*capable software*

3d printing apps	*fine software*
printing apps	*fine software algorithm*
free software	*software algorithm*
remote control software	*software algorithm optimization*
doodle3d software	*printing software details*
software design	*software auto*
software packages	*industry standard software*
software suite	*standard software*
touch software	*free slicing software*
desktop software	*slicing software slic3r*
slicing software	*excellent software*
other software	*available 3d printing software*
software experience	*free cad software*
slicer software	*software platforms*
3rd party software	*friendly newbie software*
astrobox touch software	*other slicer software*
software installation	*slicer software snap3d*
software license	*software snap3d*
verified host software	*best slicing software*
additional software	*complete software*
software tools	*complete software suite*
simplify3d software	*powerful software system*
software updates	*friendly software operation*
unique software	*software modification*
user friendly software	*beta software*
friendly software	*compatible slice software*
desktop app	*beloved free software*
3d design software	*better software*
software applications	*better software calibration*
complex software	*software calibration*
available software	*software compatibility*
advanced software	*free software packages*
free 3d modeling software	*layout software*
freedom software	*proprietary software*
software end	*software products*
software solution	*dedicated sdk software*
slice software	*sdk software*
powerful software	*software settings*
software programming	*simple modeling software*
free software upgrades	*printing software features*
software upgrades	*intelligent software*
complicated software	*intelligent software program*
zsuite software	*sophisticated software*
free 3d software	*integrated software*
software system	*different 3rd party software*
interface software	*software interface*

software bundle	*inklusive software*
suite software	*inklusive software und*
platform desktop software	*exclusive software*
desktop software suite	*printeer design software*
grade software	*specific software*
software features	*friendly softwares*
software program	*cut 3d software*
software app	*powerful 3d printing software*
cam software	*printing software solution*
great software	*machine control software*
phone app	*new software*
unique software packages	*software systems*
additional software license	*software format*
software license costs	*pc software*
controller software sets	*rapcraft software*
software sets	*rapcraft software bundle*
additional software licenses	*revolutionary software*
software licenses	*optimised firmware software*
xyz software	*software sources*
edge software	*source cad software*
customizing software	*intuitive software*
up software	*intuitive software suite*
software tutorials	*efficient software*
software side	*software adapts*
software product	*poieo3d software slice*
designing software	*software slice*
intuitive app	*software programs*
rayware software	*install software*
generation software	*slic3r software*
use cad software	*pronterface software*
3d scan software	*various control software*
scan software	*control software packages*
abc software	*cnc control software*
li software	*free software tools*
core software	*amazing design software*
innovative software	*more advanced software*
operating software	*consumer software*
cura slicer software	*3d cad software*
simple software	*expensive 3d modeling software*
awesome software	

Mobile/Web App	
apple app	*various software*
android app	*3d printing app*
web application	*desktop apps*
3d printer app	*iphone app*
printer app	*3d scanning applications*
web app	*scanning applications*
online software	*smartphone apps*
online software platform	*3d printing applications*

CNC Milling	
cnc machine	*first desktop cnc*
cnc mill	*serious cnc*
cnc machines	*serious cnc solution*
cnc router	*advanced carving*
cnc milling	*advanced carving functions*
desktop cnc	*carving functions*
precision cnc	*versatile desktop cnc*
desktop cnc system	*first cnc router*
cnc system	*je eerste cnc*
cnc routers	*je eerste cnc frees*
cnc 3d printer	*eerste cnc*
cnc solution	*eerste cnc frees*
quality cnc	*cnc frees*
stingray cnc	*first cnc machine*
own cnc	*een cnc*
cnc mills	*een cnc machine*
cnc lathe	*most versatile cnc*
professional grade cnc	*versatile cnc*
grade cnc	*versatile cnc combo*
grade cnc machines	*cnc combo*
cnc precision	*cnc combo tool*
3d carving	*small cnc*
cnc metal	*small cnc machines*
universal desktop cnc	*cnc 3d printers*
desktop cnc solution	*cnc 3d*
cnc bent	*quality cnc machine*
first cnc	*cnc match*
high quality cnc	*aircraft quality cnc*
cnc milling machines	*quality cnc machines*
cnc equipment	*speed spindle cnc*
cnc functionality	*spindle cnc*
lightweight cnc	*spindle cnc spindle*
cnc machinery	*cnc spindle*

own cnc routers	*router spindle*
own cnc router	*cnc control*
expensive cnc	*cnc control software*
cnc machine wi	*axis cnc.*
cnc router head	*cnc router parts.com*
router head	*router parts.com*
light cnc	*high end cnc*
light cnc milling	*end cnc*
cnc metalworking	*end cnc machinery*
cnc precision parts	*axis cnc*
cnc module	*cnc numerical control*
cnc carving	*cnc numerical control machine*
precision cnc router	*cnc machine programs*
router bits	*dreamhybrid cnc*
building jig cnc	*cnc machining*
jig cnc	*cnc work*
modern cnc	*house cnc*
modern cnc presses	*house cnc machine*
cnc presses	*only desktop cnc*
precision cnc machine	*full cnc*
cnc machine design	*full cnc machine*
precision custom cnc	*cnc machine shop*
custom cnc	*personal desktop cnc*
custom cnc metal	*desktop cnc machines*
cnc metal parts	

Laser Engraving	
cnc laser	*huge cnc laser*
laser engraver	*laser cut manufacturing*
laser cutter	*huge cnc laser*
laser cutting	*large laser cut*
laser engraving	*parts laser cut*
laser engrave	*laser cladding*
laser cutters	*laser cladding systems*
laser engraver module	*standard laser welding*
cnc laser	*laser welding*
mw laser engraver	*laser welding head*
laser cut wood	*wood engravings*
small engraving	*laser cutting equipment*
optional laser cutter	*laser cutting development*
plywood laser	*first laser cutter*
trinus laser engraver	*larger laser cutter*
laser engraver head	*lasercut print bed*
laser engraver slices	*lasercut wood*
powerful laser cutter	*local laser cutting*
lasercut print	*laser cutting company*
lasercut file	*laser cut parts*

Heated Bed	
hot end platform	*separate heat beds*
heat bed	*bed heating*
heated bed	*heating bed*
heating plate	*typical heated bed*
bed heat	*heated bed platforms*
heat beds	*heating pad*
bed heater	*bed heater warms*
heated build	*heated build platform*

Build Plate Materials	
aluminum plates	*aluminum bed*
glass plate	*glass bed*
aluminum plate	*square acrylic bed*
acrylic build plate	*acrylic bed*
aluminum jig plate	*ground aluminum bed*
acrylic build platform	*glass bed option*
glass build platform	*aluminum bed carriage*
mm aluminum plate	*stainless steel bed*
glass build plate	*borosilicate glass plate*

Resin Options	
light resin	*elastic resin*
several stable resins	*special dental resin*
flexible resin	*dental resin*
wax resin	*abs resin*
epoxy resin	*flexible psp resin*
polymer resin	*psp resin container*
resin types	*solid resin*
psp resin	*acrylic resin*
curable photopolymers	*high temperature polymers*
photo polymer	*clear polycarbonate*
polycarbonate abs	*thermoplastic polyurethane*
high impact polystyrene	*poly urethane*
impact polystyrene	*first polystyrene*
cast polyurethane	*polyurethane powder*
cast polyurethane parts	*polycarbonate filament*
polyurethane parts	

Resin Color Options	
black resin	*green resin*
clear resin	*red resin*
orange resin	

Curing Time	
fast curing	*post-curing time*
fast curing resins	*curing time*
fast curing speed	*curing speed*

Composite Resin	
composite resins	

Resin Tank Volume	
large tank	

Tank Heater	
strength tank heater	*tank heater*

UV Laser	
uv laser	*near uv laser*
precise uv laser	*uv laser diodes*
mw uv laser	

UV Lamp	
uv lamp	

Photomask	
photo mask	*lcd photomask*
digital photo mask	

Sublayer Photocuring	
lubricant sublayer photocuring	*sublayer photocuring*

High Definition Projector	
hd projector	*high definition projector*
high quality projectors	

Projector Lens	
Projector Lens	

Projectorless Option	
projectorless kits	*projectorless option*

Projector Size	
large projectors	*miniature projector*

Optical Lens	
correction optics	*optical end*
optical components	*glass optics*

Optical Breadboard	
optical breadboard	

Optical Power	
optical power	

Optical Sensor	
optical sensors	

Fresnel Lens	
Fresnel lens	

Lens	
fixed focus lens	*vertical lens*
focus lens	*conversion lens*
conversion lenses	*macro lens*

Camera System	
hd camera	*large format cameras*
high resolution camera	*micro camera*
video camera	*micro-camera video*
megapixel camera	*micro-camera video stream*
camera system	*compatible camera*

Support Polymer	
support polymer	*support polymer material*