Analysis of the Crucial Success Factors for Tech-Based Startups

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Abstract

For the new era of digital economy, enterprises are now facing escalating competitions and ubiquitous opportunities. How to assist enterprises in gaining competitive advantages has become a crucial issue for both academicians and practitioners. Moreover, the governmental institutes need to face a crucial issue of "allocating limited resources" especially to support startups.

This paper collects 50 external / internal tech-based startups that would either succeed or fail to find out the crucial success factors through empirical analysis. First of all, we transfer and summarize the text of the entire articles from the research institutes into quantitative data. Secondly, the correlation between crucial success factors and startups is studied. Thirdly, to solve missing value problem that has a great influence on the results of a regression analysis, we deal it with various imputation methods. Fourthly, we try to do statistical analysis with logistic regressions and exact logistic regressions. Besides, to correct the sample selection bias, we use bootstrap method to estimate statistics of the population. Our results can be an important reference not only in predicting the potentially successful startups, but also in optimizing the allocation of constrained supporting resources.

Keywords: Tech-based startups, startups, crucial success factors, KSF, limited resources

1. Introduction

Nowadays, cutting-edge technological improvements in AI, block-chain, Fintech and 5G change the ways we live. Aiming at offering the convenience and smart-living in the future, so many startups try to solve the problems by leveraging these high-end technologies. In the respect of economy, startups not only create lots of products to make life better but also help offer a lot of job opportunities in promoting economic growth. This paper takes Taiwan as an example. According to data published by the International Monetary Fund (IMF), the GDP of Taiwan is about $NT156,400. In addition, the research by BUSINESS NEXT in 2018 shows that the contribution made by 27 Taiwanese startups is over $NT420,000. That is undoubted that promoting innovation and startup entrepreneurs help to stimulate economic growth effectively. Inspired by the success stories of inventive entrepreneurs exposed by media, startups come one after another recently.

The motivation for doing this research came out with my job demands in the beginning. I have been worked in Industrial Technical Research Institute for almost 10 years. ITRI owns advanced technology (high tech.) and has incubated many startups, like TSMC, UMC, etc. Taiwan owns the advantages of semiconductor IC design, foundry, packaging and MES capabilities so we might have an opportunity to create another unicorn. ITRI is a non-profit consortium in Taiwan and parts of the resources are from Taiwan government. One of our missions is to provide technology supporting to assist domestic startups/ small and medium enterprise (SMEs) with the products commercialized. On the basis of our positioning, the research objects focus on tech-based startups. In other words, cultural innovation, design, or music creation is not my research target. In order to accelerate IoT products entering the market, my team members take the advantages of ITRI`s advanced technology to provide startups / SMEs in IoT product design and pilot production. However, most of us need to face the same issue "allocate limited resources". How to determine crucial success factors and select the potential startups/products with limited resource inevitably become an issue of first importance.

In political economy, all governments around the world recently kept giving support, including Taiwan government. They put the key topics of entrepreneurial development into major governance project but must face the problem of selection at the same time. Thus, this paper figures out the key success factors of the potential startups through data-based analysis and author's practical experience. Hopefully the result could be as a reference of decision-making and furthermore help make the maximum economic benefits.

2. Literature Review

For a long time, many essays mentioned the key success factors (KSFs) of startups but it`s pity that most essays studied one case. Chio-Juong (2017) mentioned most of the research is a case-study. Cindy (2017) took a successful case of Go-

Jek as an example, too. Fikri (2018) also chose a successful story of Go-Pay as her/his essay topic. Li-Li (2011) studied the KSFs of the company N. Even though some of the authors chose more than one case for the research object, almost most of them use qualitative research. Chun-Yu (2004) selected three private and public innovation nurturing centers as the research cases. He mentioned that he hadn`t gain the specific and clear conclusion because of region restrictions. In addition, Jui-Chun (2008) stated that most research focused on the startups that established within 3 years.

Furthermore, most of the research objects are the service industries and catering industry so we turn to collect and organized the materials from the research institutes. The KSFs gathering from them were diverse and miscellaneous. There were NEED, TREND, FUND, PRODUCT, IP, TEAM MEMBER, CONCEPT OF COST, CEO, PLAN OF BUSINESS MODEL, PROPOSAL, etc. The top four important factors which have a great effect on the results of success are NEED, PRODUCT, TREND and FUND.

After literature reviews and an overview of current knowledge, we found that most essays use qualitative research in the same way as research institute. There are several advantages of qualitative research, like being useful for practical application, offering a predictive quality, collecting some more information, eliminating the potential for bias within the data, and completing rapidly. On the other hand, qualitative research has some disadvantages as well. In view of the restrictions above, we use quantitative research. This paper collects 50 external / internal tech-based startups (1980-2016) from the platform FINDIT that would either succeed or fail.

3. Methodology and Results

3.1 Methodology and Results

In academic research, most people tend to believe what we lack in knowledge, we make up for in data, especially in the digital era. We deal with the problems of missing data, perfect prediction and sample selection bias and would like to show what we lack in proper data, we make up for in analytics.

This paper collected cases from the platform FINDIT. In Taiwan, FINDIT platform arranges the information of startups regularly, including external & internal cases. I collected cases from this platform and these startups established from 1980 to 2016. Most of them were not studied deeply so 50 cases of them became my research objects eventually.

The information of 50 cases is arranging by the experts or research institutes. Different from the way dealing with continuous variables, we use Dichotomous choice method. Dichotomous choice method is popular, due to its simplicity of use in data collection. The advantage of this method is efficient and consistency. It means that the results are the same no matter who organize and summarize. After choosing the methodology, we organize and summarize the text of the entire articles from the research institute into quantitative data and then classify into 7 variables as below.

1. item：1. software；2. hardware；3. service；4. mix
2. ex/internal：1. external case；0. internal case (Taiwanese cases)
3. need：1. meet the niche；0. not meet the niche
4. product：1. real product；0. means providing a platform or service
5. trend：1. yes；0. no
6. fund：1. yes；0. no
7. output：1. success；0. fail

Missing value problem is common in researches. In my research, there are 11 records of missing values and random. Those are distributed in 9 companies & account for 3.67 percent as Figure 1.

	item	ex / internal	need	product	trend	fund
Company C_1			1			1
Company U				1		
Company N			1			
Company T						1
Company P					1	
Company M			1			
Company S						1
E. T.					1	
Company i			1			
Company C_2						1
Total	0	0	4	1	2	4

Figure 1: Records of Missing Values

Considering that missing value problem might have a great influence on the results of a regression analysis, we deal it with four ways of imputations, including Mode Imputation, Pooled Principal Component Analysis, Principal Component Analysis and Stratified Principal Component

Method. All results are the same and consistent as Figure 2.

	need	product	trend	fund
Company C	a			h
Company U		e		
Company N	b			
Company T				i
Company P			f	
Company M	c			
Company S				j
E. T.			g	
Company i	d			
Company C				k
Total (numbers)	4	1	2	4

Solution	a	b	c	d	e	f	g	h	i	j	k
Mode Imputation	1	1	1	1	0	1	1	1	1	1	1
PCA Imputation	1	1	1	1	0	1	1	1	1	1	1
PCA Imputation (Pooled)	1	1	1	1	0	1	1	1	1	1	1
Exact logistic Imputation	1	1	1	1	0	1	1	1	1	1	1

Figure 2: Consistent with the Results from Four Ways of Imputations

After solving the missing value problem, we do statistical analysis with logistic regressions firstly. However, multicollinearity exists whenever an independent variable is highly correlated with one or more of the other independent variables in a multiple regression equation. For solving the problem of multicollinearity, we design 4-1 dummy (d1, d2, d3) as Figure 3.

	d1	d2	d3
X1 (software)	0	0	0
X2 (hardware)	1	0	0
X3 (service)	0	1	0
X4 (mix)	0	0	1

Figure 3: Item, d1, d2 and d3

Then we do statistical analysis with logistic regressions. Unfortunately the result shows perfect prediction problem and there are 28 cases left only. For solving perfect prediction problem, we substitute exact logistic regressions for logistic regressions. Significance indicated by * at the 10%, ** at the 5%, and *** at the 1%, variables of d2, ex/internal, and need are statistically significant. It shows that the log odds of d2 is 2.50 decreased. The log odds of ex/internal companies is 1.78 decreased. The log odds of need is 2.61 upper. See Figure 4.

The results

Variable	Exact logistic regression	
	All variables	
d1	-	-
d2	-3.37*** (0.003)	-2.50** (0.03)
d3	0.92 (0.57)	-
ex/internal	-3.28** (0.03)	-1.78* (0.10)
need	3.63** (0.04)	2.61** (0.03)
product	-2.20 (0.20)	-
trend	1.61 (0.33)	-
fund	-	-

*P≦0.1, **P≦0.05, ***P≦0.01

Figure 4: The Results of Exact Logistic Regressions

In addition, we consider sample selection bias. The average of success survival rate in Taiwan is 57%, counting by Small and Medium Enterprise Administration, Ministry of Economic Affairs (Taiwan government). Compared with the data from Taiwan government, failure rate of my research is 22% and is much lower. From my experience, failure cases might not be exposed. On the other hand, failure cases usually can`t attract research institutes so they have a greater chance of being ignored.

So considering the existence of sample selection bias, we use bootstrap method which is a resampling technique used to estimate statistics on a population by sampling a dataset with replacement to correct the bias. We take the average of success survival rate and failure rate as prior knowledge. This means that I withdraw one case from success cases and put it back. Repeat the steps for 57 times. After that. I withdraw one case from failure cases and put it back for 43 times. So I can construct 100 records for a set. Then repeat the steps as above for 50 times and do statistical analysis with exact logistic regression for 50 times as well. According to the research, the result shows that variables of d2、ex/internal、need、fund are significant. Positive and negative signs of regression coefficient are consistent even after correcting sample selection bias. The only difference is that the variable of fund becomes significant after correcting. Thus, the modified forecasting model is the log odds of success = -3.260*d2 -4.331*ex/internal +3.646*need +2.873*fund. See Figure 5.

the mean of d2 in regression analysis	-3.260
the mean of ex/internal in regression analysis	-4.331
the mean of need in regression analysis	3.646
the mean of fund in regression analysis	2.873

Figure 5: The Mean in Regression Analysis

3.2 Predict the Success Probability

On top of that, in order to show a feasibility study, we would mention how to predict the success probability through our model. We take MB Company as an example next. This company established in 2016 in Taipei, Taiwan and its product is IoT Music Box. After analyzing this company, the information coming out includes an internal case, mix of the item, meeting the niche market, and having fund. The information above is converted into the corresponding variables of this paper (internal, item, need, fund) = (0, 0, 1, 1). The model is as below.

The log odds of success for MB Company
= -3.260*0 -4.331*0 +3.646*1 +2.873*1
= 6.519

That we change the log odds into the success probability is as below.

Probability of success for MB Company = e6.519 / (1+e6.519) = 0.998

Based on the result, we predict that MB Company is a highly potential and successful startup.

4. Conclusion

4.1 Find a Pain Point (need) Which is a Scalable Niche as Well

According to the forecasting model, need of the crucial factor is really important. Startups should find a pain point and it should be scalable enough. In fact, from my practical experience, most startups that I visited in Taiwan didn`t spend much time identifying and defining marketing opportunities and problems or they had less resources to do that. So take Taiwan as an example, Taiwan market is small. If startups want to be another unicorn, they should find a scalable niche. Of course, considering that startups might lack resources in the beginning, they could separate planning into phases. This allows them to track immediate improvements while evaluating progress toward eventual goals and targets.

4.2 The Trend of Products in the Future Might be a System Integration that Combines Software＋Hardware＋Platform＋Service

According to forecasting model, the log odds of d2 is 3.260 decreased so I think startups should follow the trend. The trend of products in the future might be a system integration that combines software ＋ hardware ＋ platform ＋ service. Actually, many IoT products which are e-commerce, app, or platform belong to the kind of software / Software system integration. Entry barrier is low but these kinds of IoT products have advantages of cross-regional and time limitless. A short term goal is that startups might entry market quickly, seize market share and improve product visibility. Besides, create brand stickiness to make customers staying with the products through other marketing strategies.

However, entry barrier is still the major factor of market structure from the economical angle. Middle term and long term goals are that startups might focus on software + hardware + platform + service integration system. Startups may own their core technologies and, meanwhile, they should continue creating added value in order to have higher income.

4.3 The Last Mile-Successful Commercialization by Providing One-Stop Service

The KSFs gathering from research institutes and literatures were diverse and miscellaneous. From my practical experience, some factors had less influence on the results of commercialization. The major reason is that startups lack not only resources in the early stage but also a professional integrator. They don`t have enough abilities/experiences to deal with integration works. In fact, finance, legal, business model design, prototype, commercialization and more are necessary processes for entering the market. So take Taiwan as an example. Government should provide a total solution of a one-stop service that integrate all resources (including concept to commercialization) to assist startups.

References

Chueh, C. J. (2017). *The study of key failure factors for Taiwan small and medium startup enterprises* (Masters thesis). Fu Jen Catholic University, New Taipei, Taiwan.

Dear, R. E. (1959). A Principal Component Missing Data Method for Multiple Regression Models. *System Development Corporation*, Technical report SP-86.

Ismail, F. (2018). *A success story of a fintech startup: A case of Go-Pay to be the fastest growing digital wallet in Indonesia* (Masters thesis). National Yang-Ming Chiao Tung University, Hsinchu, Taiwan.

Lin, C. Y. (2004). *Critical success factors of technology incubators：A case study* (Masters thesis). Chung Yuan Christian University, Taoyuan, Taiwan.

Mehta, C. R., and Patel, N. R. (1995). Exact logistic regression: Theory and examples. *Statistics in medicine, 14*(19), 2143-2160.

Rubin, D. B. (1981). The bayesian bootstrap. *The annals of statistics, 9*(1), 130-134.

Su, C. (2017). *A success story of a startup: A case of Go-Jek to be the first unicorn in Indonesia* (Masters thesis). National Yang-Ming Chiao Tung University, Hsinchu, Taiwan.

Su, J. C. (2008). *The relationship between eEntrepreneurial competency and entrepreneurial performance- An example of the technology-based entrepreneurs* (Masters thesis). Shih Chien University, Taipei, Taiwan.

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