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Development of an Investability Prospect Score in Indonesia: Early Stage Digital Startup

Deny Rahardjo[a], Sugiarto[b], Gracia Shinta S. Ugut[c], Edison Hulu[d], [a]Doctoral Program, Universitas Pelita Harapan, Indonesia, [b]Faculty member of Universitas Prasetiya Mulya, Indonesia, [c]Dean of Business School, Universitas Pelita Harapan, Indonesia, [d]Lecturer, Graduate School, Universitas Pelita Harapan, Indonesia. Email: [a]DR70020@student.uph.edu, [b]Prof.sugiarto@gmail.com, [c]gracia.ugut@uph.edu, [d]edison.hulu@lecturer.uph.edu

Research shows that radical innovation is more likely to come from smaller companies such as ‘startups’. Startup is drawing a lot of attention given the growth potential for both entrepreneurs and investors. One of the most challenging aspects in this venture is the investability readiness level of the startup as it is difficult to assess the usual financial aspect such as cash flow in the initial loss-making company with no or limited financial data. The authors developed an Investability Prospect Score (IPS) based on a similar approach from Altman’s Z-score by using a Multiple Discriminant Analysis (MDA) method. Responses to questionnaires from a cross sectional online survey were then used to identify factors such as industry structure, product readiness, founders’ background and management structure, financial robustness and risk management towards investment readiness in Indonesia and the early stage digital startups ecosystem. The contribution aspect of this article is to provide a structured approach in identifying the readiness status of startup for investment. This could also be used as additional determinants towards a valuation model such as real options which is deemed to be more suitable in dealing with the flexibility and uncertain nature of digital startups.

Key words: *Investability prospect, startups, digital, innovation, investment, valuation, risk analysis, venture capital.*

Introduction

Research shows that radical innovation is more likely to come from smaller companies such as 'startups' which created most of the new jobs from 2000 to 2010 in the US (Christensen, Raynor, Rory, & McDonald, 2015; Fairlie, 2012). They spur productivity, efficiency and contribute to a country's overall competitiveness (Cumming, Johan, & Zhang, 2014). A study conducted by Kearney (2017) stated that the digital startups scene in South East Asia was growing fast with more than $10B invested, dominated by Singapore and Indonesia. Indonesia as the 4th biggest population in the world with more than 250 million people and more than 100 million smartphones, has also seen rapid growth in the number of startups in the last few years (Davies & Silviana, 2018).

Assessing investability readiness level and valuation of company early in the life cycle is difficult and subjective, partly because of the absence of operating history, financial information and also because most young firms do not make it through these early stages to success (Brealey, Myers, & Allen, 2006; Damodaran, 2009; Damodaran, 2001).

The authors are interested to understand what factors would entice investors in investing in the early stage startup despite knowing the inherent risks coming from such ventures especially in the Indonesian context. The main research question is, is there any categorical difference in factors that would influence a startup receiving funding (Investability Prospect Score or IPS)? The study will investigate using the bankruptcy-prediction model of Altman's Z-score (Altman, 1968).

Literature Review

Digital startup or 'Tech Startup' refers to a new company with novel business ideas that embrace new technology innovation as a key business differentiator to facilitate rapid growth (Nalintippayawong, 2019). It exhibits common attributes such as high growth, highly innovative, trying to reach large or global markets, poses higher risk and typically with the major portion of the capital being from external source funds such as angel investors and venture capital (VC) (Baum & Silverman, 2004; Brealey et al., 2006; Florin, Dino, & Huvaj, 2013; Tanev, 2012).

The founders of a startup need to develop solid and scalable business plans supported with sufficient capital to realise their idea (Reinfeld, 2018) in which they would typically need to establish a relationship with investors to gain sufficient capital to ensure its survival (Miloud, Aspelund, & Cabrol, 2012). Improper selection and valuation strategies that lead to dissatisfactions among the founders and investor is a contributing factor towards the high failure rate of startups (Zacharakis, Erikson, & George, 2010).

The main key objective of any firm is stakeholder wealth optimisation (Friedman, 1962) hence it is important given these uncertainties for investors to assess the potential of startups and select their investments. It is also equally important for founders of startups to understand their company's valuation in order not to give away a portion of the company unnecessarily which would lead to dissatisfaction and demotivation (Miloud et al., 2012).

Common Startups Valuation Formula

Valuation process in any venture or company is always complex due to the diversity of contributing factors (Brealey et al., 2006). It is a lot more than a typical pure financial consideration such as tending a balance sheet, income statement and cash flow (Damodaran, 2006). This is especially true in analysing early stage startup where financial information is either rare or even non-existent (Goldman, 2008; Kumar, 2015). Technology-based startups need a significant amount of financial resources from investors to further develop their technologies (Zheng, Liu, & George, 2010). It has been heavily researched that investing in a new venture such as early stage startup involves a high degree of risk of failure and uncertainties (Ruhnka & Young, 1991).

Discounted Cash Flow (DCF) is quite commonly used for startup valuation especially in the growth stage of startups once the revenue is generated hence the future cash flow can be forecasted (Damodaran, 2018). The most common limitations of DCF method are the difficulty in estimating future cash flow, finding appropriate benchmark company and the fact it cannot cater for the dynamic, flexibility and uncertainty nature of digital startups (Abrams, 2010; Rogers, Gupta, & Maranas, 2002). For early stage digital startups that requires initial investment such as for R&D, DCF value would be most likely a negative one which would discourage the investors and often undervalue projects (Putri & Fujiwara, 2015; Trigeorgis, 1993). Another striking limitation is the single discount rate used in DCF for all periods as typical startups would experience different stages ('stepping stone') within the business life cycle that represent different risks or discount rates (Berkery, 2008).

The real options fill the gaps left by a more prominent method such as DCF (Tamayo-torres, Ruiz-moreno, & Verdú, 2010). It offers managerial flexibility to optimally time an investment so that its value is maximized (Čirjevskis & Tatevosjans, 2015) and has been used to valuate investment and opportunities in many prominent multi-national companies such as Kone and Boeing (Jyväskylän Yliopisto Kauppakorkeakoulu, 2015). In Cox-Ross-Rubinstein' binomial model, variance or volatility (σ) is a standard deviation of the profit on the basic equity (Cox, Ross, & Rubinstein, 1979; Gupta & Chevalier, 2002) and one of the factors to determine option value. Other factors such as value of the underlying, implementation costs of the option, time till expiration, risk free rate and the value lost over option's duration (Čirjevskis & Tatevosjans, 2015). While real option theory is a very promising approach for valuating digital startups investment, most managers still use the traditional such as DCF, because of the complexity and lack of knowledge about real options prevents managers from utilising this salient method to value their investment (Jin & Sanders, 2002).

As the focus is on early stage startup that typically does not have enough traction and financial information or figures, a typical business valuation model might not be applicable (Bell, 2014; Miloud et al., 2012). "In the process, we argue that the venture capital approach to valuation that is widely used now is flawed and should be replaced (Damodaran, 2009)". Hence there is a need to have something in place as a necessary condition prior for valuation towards investment decisions in early stage digital startups.

Investability Prospect Score (IPS)

Investor and startup founders need to have input before deciding on a partnership. Personal traits, as argued by Valliere and Peterson (2007), have an impact on both investor and start-up founder decision-making. The similarity of values and characteristics influence the investment decision (Cardon, Mitteness, & Sudek, 2017; Ding, Sun, & Au, 2014). Other examples such as industry growth rate, product uniqueness, background of the founders, management structure and personal traits compatibility between founders and investors (Miloud et al., 2012).

The Investability Prospect Score (IPS) indicates the startup's overall readiness or rating in terms of being funded or invested by the potential investors. The IPS concept was adopting the approach of Altman's Z-score that is prominently used as a bankruptcy-prediction tool (Altman, 1968). It was originally based on the work of Beaver (1966) that used 30 financial ratios to predict financial failure five years prior to the event. While there have been other failure prediction alternative models, Altman's Z-score continues to be used worldwide as a main or supporting tool for bankruptcy or financial distress prediction over the last 40 years (Altman, Iwanicz-Drozdowska, Laitinen, & Suvas, 2017; Siddiqui, 2012).

It used combinations of selected financial ratio analysis one-year prior to bankruptcy on each 33 bankrupt and non-bankrupts selected publicly held manufacturing companies in United States using a Multiple Discriminant Analysis (MDA) model to derive the discriminant function as the following:

$$Z = 0.012\ X_1 + 0.014\ X_2 + 0.033\ X_3 + 0.006\ X_4 + 0.999X_5 \qquad (1)$$

where X1 = Working capital/Total assets

$X2$ = Retained Earnings/Total assets
$X3$ = Earnings before interest and taxes/Total assets
$X4$= Market value equity/Book value of total debt
$X5$ = Sales/Total assets
Z = Overall discriminant score*

*Scores that add to a z-score<1.81 have a high probability of bankruptcy, while scores>2.67 represent financial soundness. The grey area or zone of ignorance exists when firms have z-scores between 1.81 and 2.67.

Altman and Saunders (1997) later extended Altman's work in 1968 to product model for private firms that resulted in the following revised Z'-score model:

$$Z' = 0.717X^1 + 0.847X^2 + 3.107X^3 + 0.420X^4 + 0.998X^5 \quad (2)$$

where X4 = Book value of equity/Book value of total liabilities, with the other variables the same as those in the original (1968) Z-Score model with area between 1.23 and 2.9 as zone of ignorance (Altman et al., 2017). Altman's Z-score then became seminal work that has been cited and further researched and was catered even for the non-manufacturing sector to predict bankruptcy in the hospitality sector, service industry, publicly listed companies, and banks alike, to predict if the business will have a downfall (Gu, 2002; Siddiqui, 2012).

Multiple Discriminant Analysis (MDA) is a statistical technique used to classify an observation into one of several *a priori* groupings dependent upon the observation's individual characteristics (Altman, 1968). MDA is used to study the differences between two or more objects with respect to several variables simultaneously (Klecka, Iversen, & Klecka, 1980). The main goal of discriminant analysis is to predict group membership from a set of predictors (Tabachnick, Fidell, & Ullman, 2007) and to a greater extent, sensitive to the occurrence of outliers (Mihalovič, 2016). The underlying discipline is discriminant analysis with its main use being to validate and predict classification of categorical dependent variable based on its independent variables (Sugiarto, 2017a).

$$Z = C_1X_1 + C_2X_2 + C_3X_3 + \ldots + CnXn, \quad (3)$$

Where
$C_1; C_2; C_3; \ldots, Cn$ = discriminant coefficients;
$X_1; X_2; X_3; \ldots, Xn$ = classifying variables (i.e. financial ratios)

There were later numerous researchers that attempted to predict business failures using MDA modelling with different data sets such as Deakin (1972). They used 14 ratios to predict business failures as early three years in advance, and Blum (1974) constructed a 'failing company model' with 94% accuracy rate. Dimitras et.al (1996) performed a comprehensive literature review and concluded that MDA was the predominant method to predict business failures.

Similar with Z-score, 'Investability Prospect Score' (IPS) would be generated for a cross sectional data set which is representing the investability prospect startup of each startup. The authors will use an MDA model with two categories 'funded' and 'not funded' for the startups' group of samples.

Research Model

Participating in the 'right' industry as a clear and growing target market is very crucial as has been mentioned in many research papers. Startup founders need to understand the customer segment that represents size of total addressable market to develop an appropriate marketing mix and to generate interests among investors. If the market size is too small then it prohibits the startup growth (Nalintippayawong, Waiyawatpattarakul, & Chotipant, 2018). Industries with high product differentiation have less competitors which increase venture performance (Porter, 1980). It is also viewed as less risky compared with simple projects in low growing markets, hence indicating the level of volatility (Delmar & Shane, 2006; Fazekas, 2016; Miloud et al., 2012).

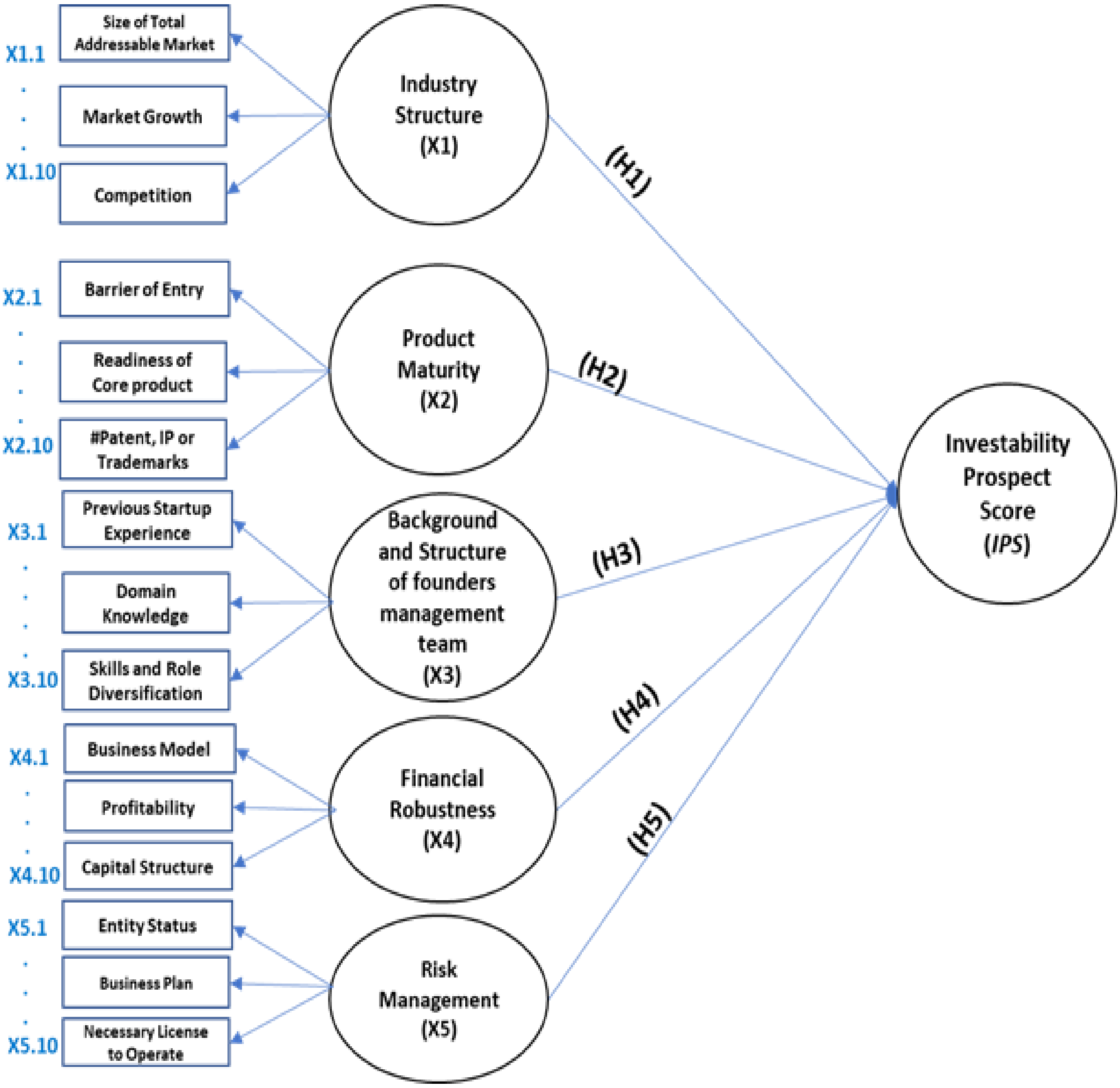
Product maturity and differentiation is one of the most important elements positively related to company performance, and it would set the entry barrier level to the market and compete especially when there is an advantage to be the first mover in the market (Caves, 1972; Cusumano, 2013; Hunt, Mitchell, Phaal, & Probert, 2004; Nalintippayawong et al., 2018; Porter, 1980; Sandberg, 1986). It is more so for those whose products granted patents, as the likelihood of funding such ventures would increase even more (Baum & Silverman, 2004).

Startup founders and their team could serve as a competitive advantage for the business by having experience in a similar industry which would influence the company performance (Siegel, Siegel, & Macmillan, 1993). Argued that the prior work experience of the founder could contribute to skills that are favourable across a broad scope of occupational activities which lead to current company performance. Other than founders, the management team are also believed to have impacted on the company performance with each individual in those teams, and also need to have complementary quality for the success of the team (Carpenter & Fredrickson, 2001; Muzyka, Birley, & Leleux, 1996; Roure & Keeley, 1990). The team that previously worked together would have a better understanding of the coordination and communication style that can lead overall to a company's growth (Eisenhardt & Schoonhoven, 1990).

Financial robustness mainly depends on the correct business model being adopted by the startup which relates to the operating plan of a startup that indicates form, income channel, stability, and ability to compete with other startups (Nalintippayawong et al., 2018). It is evident that most young firms do not make it through these early stages to success (Brealey et al., 2006; Damodaran, 2006, 2009). Hence to have proper financial planning especially in regard to cash flow and capital structure is required to not only manage the funds from investors but also to go through the 'valley of death' until the startup can generate enough revenue and cash to sustain its operation (Damodaran, 2009).

Investing in a new venture such as early stage digital startup involves a high degree of risk of failure and uncertainties with half of new ventures failing within the first two years of its inception (Song, Song, & Parry, 2010). It is at the interest not only for the potential investors but also for founders themselves to setup the company in the proper manner by following local rules and regulation supported by necessary agreement such as founder or shareholder agreement (Desaché, 2015). Many companies went out of business due to weak governance and risk management (Ding et al., 2014; Drover et al., 2017; Rodriguez, 2006). It has also been researched that having clear and solid business plan is very much preferred by investors in reducing their risk. This includes but not limited to startup's ability in dealing with threats from more prominent competitors and scale-up plan to grow the business (Ruhnka & Young, 1991; Shad & Lai, 2015).

Figure 1. Research Model



$$IPS = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 \quad (4)$$

Note:

IPS	= Investability Prospect Score
X1	= Industry structure
X2	= Product maturity
X3	= Background and structure of founders' management team
X4	= Financial robustness
X5	= Risk management

Research Hypothesis

The authors investigated the research question which is, are there any categorical differences of factors that would influence a startup to receive funding (Investability Prospect Score or IPS)? The study mostly departed from the model used by venture capital (Miloud et al., 2012) that could also be applied towards other investors' investment in the context of early stage Indonesia digital startups. It is expected that the conclusions can be used to answer the research question and to analyse evidence according to the hypothesis as described in the following table, Table 1.

Table 1: Research Hypothesis

No	Hypothesis
Hypothesis 1	The industry structure of the startup has positive contribution or impact towards Investability Prospect Score.
Hypothesis 2	The degree of product maturity has positive impact towards Investability Prospect Score.
Hypothesis 3	Startup with founders who have been successful in growing another startup previously supported with complementary management team would have positive contribution or impact towards Investability Prospect Score.
Hypothesis 4	An early stage startup founded with a robust financial would have positive contribution or impact towards Investability Prospect Score.
Hypothesis 5	Startups with proper risk management would give more confidence for investor to invest hence a higher Investability Prospect Score.

Research Method

The challenge in getting the data was quite prevalent as startup founders were rarely willing to provide the requested information nor often able to provide financially related information. In addition to that, startup is a rather new phenomena in Indonesia (Davies & Silviana, 2018), with the key focus of many startups being around survivability and getting an innovative product or service launched to the market. The authors decided to approach a few prominent angel investors associations in Indonesia such as Angel Investor Indonesia Network (ANGIN) and Indonesia Fund Festival (IFF) as they were very open for the collaboration idea and looking forward to using the outcome of this research.

The research focused on Indonesia-based early stage digital startups regardless of the background of the investors and founder population. It was limited to only digital or technological startups that show few common attributes such as fast growth, highly innovative, trying to reach a large or global market (Tanev, 2012), posing higher risk and typically relying on the major portion of the capital from external source of funds such as angel investors and venture capital (VC) (Baum & Silverman, 2004; Florin et al., 2013). Early stage startup is typically around 3 years since at its inception that has received external investment at least once (outside self-funding initial investment from the founders or bootstrapping) (Brealey et al., 2006).

There were more than 1,500 of early stage digital startups with 100 having received a minimum of one investment, based on the data collated from www.crunchbase.com based on the following conditions:

- Headquarters location: includes any of "Indonesia"
- Operating status: equals of "Active"
- Number of funding rounds: greater than or equal to "1"
- Incorporation date since 1 October 2016 (three years from the access date of data from www.crunchbase.com).

The authors decided to adopt "Small Sample Techniques" as per article published by the research division of the National Education Association (Bartlett, Kotrlik, & Higgins, 2001).

$$s = X_2\ NP(1- P) \div d_2\ (N -1) + X_2\ P(1- P) \quad (5)$$

Note:
s = required sample size
X2 = the table value of chi-square for 1 degree of freedom at the desired confidence level (3.841)
N = the population size
P = Population size (100 taken from www.crunchbase.com)
d = the degree of accuracy expressed as a proportion (0.05 or 5%)

From the population size of 100, it was concluded that the authors needed to have 80 startups as a sample from ANGIN and IFF database of early stage digital Indonesia startups which was taken using unrestricted or simple random sampling technique (Sugiarto, 2017b). The authors used online survey tools of www.sogosurvey.com to collect primary data from startups that have been identified in the sampling process.

The authors adopted similar Multiple Discriminant Analysis (MDA) to derive Investability Prospect Score (IPS) which is similar with Altman's Z-score, hence it would gather 40 'funded' and 40 'non-funded' startups from the sampling pool. The definition of 'funded' startup are those startups that have received funding or very strong interests for investment from the investors during the fund-raising events organised by ANGIN and IFF (in this case was normally marked with the investors raising their green flag during the event).

An online questionnaire with 53 questions was prepared prior by using mixed measurement scale techniques such as category and Likert scale (Sugiarto, 2017b). Similar with Z-score, 'Investability Prospect Score' (IPS) would be generated for a cross-sectional data set which is representing the investability prospect startup of each startup. The authors used MDA model with two categories of 'funded' and 'not funded' of the startups' group of samples.

Results

The online survey was sent through IFF and ANGIN administrators from 10 January 2020 to 10 February 2020 to the startups founders' databases. The survey yielded 96 responses in which almost all came from IFF database. There were 80 valid responses as part of data editing processes by removing incorrect data such as the non-startup respondent (i.e. venture capital), inconsistent responses and data from startups that were founded more than or equal to five years ago. The valid 80 responses were then mapped into the startup type table given by IFF which resulted to 40 startups of type-1 (funded) and 40 startups of type-2 (non-funded).

The respondents were mostly male (81.25%) compared with the female in which all of them claimed to be one of the founders of the startup (100%). The age groups were mostly between 21-30 years old and 31-40 years old (in total around of 86%). Most of the startups were founded around 2 years prior to the survey (42.5%) with equal distribution from either 1-year-old or 3-year-old.

As the intention was to use MDA as data analysis tool, there was a need to convert ordinal scale data (value of 1-5) by assuming equal distance between ordinal number of 1 to 5. To convert into ratio scale data, each data response is divided by 5 (i.e. from 1 to 1/5 or 0.2, from 2 to 2/5 or 0.4 and so on). The authors also decided to take out all nominal indicators as they were not suitable to being analysed further. They were used to indicate a profile of the respondents which claimed to have founder or shareholder agreements in place (61.25%) and equipped with proper business license and tax registration number (80%).

The authors focused on a normality test based on Shapiro-Wilk in which while we did not have issues with X1, X2 and X4 their values are higher than 0.05 (which means that we cannot reject H0 as data is normally distributed), so we needed to review X5 and X3 by removing their outliers. The remainder of 70 responses (35-funded and 35-not funded) were normally distributed indicated by their Shapiro-Wilk's normality test with the values of higher than 0.05 which is as the following, in Table 2:

Table 2: Revised Normality Test

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
X1	.096	70	.180	.973	70	.134
X2	.114	70	.026	.984	70	.539
X3	.087	70	.200*	.966	70	.053
X4	.074	70	.200*	.981	70	.384
X5	.121	70	.013	.968	70	.073

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

To be considered as a reliable data, the Cronbach's alpha value of a variable needs to be more than 0.6 (Sekaran and Bougie, 2016). The result later showed Cronbach alpha (based on standardized items) values of all variables are 0.715 (> 0.6) hence we can conclude that data is reliable, and we do not need to remove any variable from our measure to increase the inter-item consistency (Sekaran and Bougie, 2016).

Table 3: Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.708	.715	5

The authors performed an independent sample t-test to accept or reject the statistical hypothesis with a degree of freedom (df) of 68 (70-2) and a level of significance $\alpha = 0.05$ with the null hypothesis H_0 defined as the respective independent variable which has no impact towards investability (funded or not funded). We will reject H_0 if the calculated value is less than critical value (Sekaran and Bougie, 2016). As shown in the following table, except for product maturity (X2), in which its Sig. of 0.192 is bigger than 0.05, we can reject H_0 of X1, X3, X4 and X5. In other words, all independent variables except product maturity (X2) would have impact towards Investability (funded or not funded) (Table 4).

Table 4: Independent Sample Test - Hypothesis Testing

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
X1	Equal variances assumed	1.401	.241	4.412	68	.000	.07771	.01761	.04257	.11286
	Equal variances not assumed			4.412	65.375	.000	.07771	.01761	.04254	.11289
X2	Equal variances assumed	.006	.939	1.316	68	.192	.02629	.01997	-.01356	.06613
	Equal variances not assumed			1.316	67.490	.193	.02629	.01997	-.01357	.06614
X3	Equal variances assumed	.177	.676	2.747	68	.008	.03600	.01311	.00985	.06215
	Equal variances not assumed			2.747	67.797	.008	.03600	.01311	.00984	.06216
X4	Equal variances assumed	1.007	.319	2.474	68	.016	.05657	.02287	.01093	.10221
	Equal variances not assumed			2.474	65.170	.016	.05657	.02287	.01090	.10224
X5	Equal variances assumed	3.017	.087	3.991	68	.000	.08171	.02048	.04086	.12257
	Equal variances not assumed			3.991	67.583	.000	.08171	.02048	.04085	.12258

The valid 70 sample data (35-funded and 35-not funded) was then analysed using 2-level MDA per independent variable to estimate its respective value that produce the following formula:

$$X1 = 0.492\ Q1 + 0.395\ Q3 + 0.389\ Q6 + 0.519\ Q10 \quad (6)$$
$$X2 = 0.602\ Q2 + 0.738\ Q3 \quad (7)$$
$$X3 = 0.336\ Q1 + 0.699\ Q3 + 0.335\ Q4 \quad (8)$$
$$X4 = 0.672\ Q1 + 0.159\ Q2 + 0.358\ Q3 + 0.195\ Q4 \quad (9)$$
$$X5 = 0.236\ Q2 + 0.198\ Q3 + 0.305\ Q4 + 0.638\ Q5 + 0.258\ Q7 \quad (10)$$

The last step is to perform MDA on the MDA factor of all independent variables (X1, X2, X3, X4 and X5) as shown below:

Table 5: Tests of Equality of Group Means Independent Variables

	Wilks' Lambda	F	df1	df2	Sig.
X1	.809	16.033	1	68	.000
X2	.794	17.687	1	68	.000
X3	.812	15.730	1	68	.000
X4	.878	9.456	1	68	.003
X5	.650	36.609	1	68	.000

From the information in Sig. column, we can conclude all independent variables of X1, X2, X3, X4 and X5 are significant variables as their significant values are < 0.05. This is also to conclude that we can reject all null hypotheses (H_0) and that all independent variables are indeed having an impact or influence towards Investability Prospect Score (IPS).

$$IPS = 0.302\ X1 + 0.272\ X2 + 0.254\ X3 + 0.181\ X4 + 0.577\ X5 \qquad (11)$$

Discussion

As per a similar approach used in Altman's z-score to predict bankruptcy, IPS was analysed to understand the categorical differences between type 1 (funded) and type 2 (not funded).

Table 6: Descriptive IPS

	Type			Statistic	Std. Error
IPS	1	Mean		.7380	.01301
		95% Confidence Interval for Mean	Lower Bound	.7116	
			Upper Bound	.7644	
		5% Trimmed Mean		.7425	
		Median		.7400	
		Variance		.006	
		Std. Deviation		.07700	
		Minimum		.54	
		Maximum		.85	
		Range		.31	
		Interquartile Range		.12	
		Skewness		-.699	.398
		Kurtosis		.400	.778
	2	Mean		.6617	.01487
		95% Confidence Interval for Mean	Lower Bound	.6315	
			Upper Bound	.6919	
		5% Trimmed Mean		.6667	
		Median		.6800	
		Variance		.008	
		Std. Deviation		.08800	
		Minimum		.37	
		Maximum		.82	
		Range		.45	
		Interquartile Range		.10	
		Skewness		-1.163	.398
		Kurtosis		2.340	.778

IPS Type 1 (funded) has the mean of 0.7380 with min and max values of 0.54 and 0.85 respectively. IPS Type 2 (not funded) has lower value of mean (0.6617) with min and max values of 0.37 and 0.82. IPS type 1 has narrower range of 0.31 compared with 0.45 from IPS type 2. Based on this simple analysis, it can be concluded that IPS of greater than 0.82 falls into 'funded' category and startups with an IPS lower than 0.54 are part of the 'not funded' category. The grey or confusion area is between 0.54 and 0.82 where any sample could be either type 1 or type 2.

The next step was to identify sample observations which fall into the grey area for Type 2 (not funded) with the IPS value higher than or equal to 0.54 and Type 1 (funded) with the IPS value less than or equal to 0.82 (Table 7).

Table 7: Startups in Grey Area

StartupID with Type 1 <= 0.82	IPS	StartupID with Type 2 >= 0.54
15	0.54	
10	0.55	2
	0.56	3
	0.57	8
	0.58	12
	0.60	56
	0.61	22
	0.62	55
34	0.64	11
54,31	0.66	4,9
6	0.67	38,67,43
44,7,13	0.68	21,37
60,69	0.69	68,19,39
	0.70	32,65,47,57
66,61	0.71	18,62
29,64	0.72	5
42	0.73	45,30
23,28	0.74	41
24	0.75	49
59	0.76	
14,36,33,40	0.77	17
	0.78	35
20,50,53	0.80	
46	0.81	
58	0.82	51

Similar to an approach taken by Altman (1968), the final step was to group the startups in the grey area into the range values of IPS in order to find the minimum number of startups in that particular range. From the following table, it was concluded that the best critical value fell between 0.58-0.62 hence 0.60 as the midpoint of interval was chosen as an IPS value that discriminates best between the funded and not funded startups (Table 8).

Table 8: Number of startup in Grey Area using various IPS value as criterion

Range	Number of Startups in Grey Area	StartupID
0.54 - 0.58	7	2,3,8,10,12,15
0.58 - 0.62	4	12,22,55,56
0.62 - 0.66	7	4,9,11,31,34,54,55
0.66 - 0.70	22	4,6,7,9,13,19,21,31,32,37,38,39,43,44,47,54,57,60,65,67,68,69
0.70 - 0.74	17	5,18,23,28,29,30,32,41,42,45,47,57,62,65,66,61,64
0.74 - 0.78	12	14,17,23,24,28,33,35,36,40,41,49,59
0.78 - 0.82	7	20,35,46,50,51,53,58

Robustness is the ability to reproduce the method under different circumstances without the occurrence of unexpected differences in obtained result (Vander Heyden, Nijhuis, Smeyers-Verbeke, Vandeginste, & Massart, 2001). To test the robustness of the model, the authors performed model variation or alternative model (Neumayer & Plümper, 2017) by eliminating the least significant variable of X4 (financial robustness) and to run MDA again which showed that all independent variables of X1, X2, X3, and X5 are still significant variables as their significant values are < 0.05.

Table 9: Tests of Equality of Group Means Independent Variables (alternative model)

	Wilks' Lambda	F	df1	df2	Sig.
X1	.809	16.033	1	68	.000
X2	.794	17.687	1	68	.000
X3	.812	15.730	1	68	.000
X5	.650	36.609	1	68	.000

Table 10: Standardized Canonical Discriminant Function Coefficient

	Function
	1
X1	.305
X2	.327
X3	.222
X5	.634

$$IPS' = 0.305\ X1 + 0.327\ X2 + 0.222\ X3 + 0.634\ X5 \qquad (12)$$

Table 11: Descriptive Statistic (alternative model)

	Type			Statistic	Std. Error
IPS	1	Mean		.7451	.01390
		95% Confidence Interval for Mean	Lower Bound	.7169	
			Upper Bound	.7734	
		5% Trimmed Mean		.7511	
		Median		.7600	
		Variance		.007	
		Std. Deviation		.08223	
		Minimum		.51	
		Maximum		.86	
		Range		.35	
		Interquartile Range		.11	
		Skewness		-.919	.398
		Kurtosis		1.227	.778
	2	Mean		.6700	.01633
		95% Confidence Interval for Mean	Lower Bound	.6368	
			Upper Bound	.7032	
		5% Trimmed Mean		.6759	
		Median		.6900	
		Variance		.009	
		Std. Deviation		.09659	
		Minimum		.34	
		Maximum		.83	
		Range		.49	
		Interquartile Range		.10	
		Skewness		-1.275	.398
		Kurtosis		2.750	.778

In the revised model of IPS’, type 1 (funded) has the mean of 0.7451 with min and max values of 0.51 and 0.86 respectively where IPS’ Type 2 (not funded) has lower value of mean (0.6700) with min and max values of 0.34 and 0.83. The grey area of IPS’ (0.51 – 0.83) is somewhat similar with the original area of IPS (0.54 - 0.82) which showed that the original model of IPS is somewhat quite robust despite removing its least significant independent variable.

Conclusion

This study found that IPS could be used to indicate readiness level of investment based on the startup relevant indicators of each independent variables. Investors could consider factors or variables in this research, in addition to or as alternatives of the typical 'gut-feeling' and subjective approach when making the right decision to potentially invest and determine the valuation involved (Goldman, 2008). Investors are able to use it to assess the risks and opportunities to invest in startups (Nalintippayawong et al., 2018). Startup founders would also be able to review the readiness by looking at the investability prospect score model prior to approaching potential investors.

This would increase the potential to be invested by proposing a more reasonable valuation that would be enough for the company to build the products and gain traction, without losing too much equity unnecessarily, especially in the beginning of the ventures. By understanding the common variables, the founders could also use it to choose the right type of industry and business model that would produce better valuation and a higher chance of success. In other words, it provides a guideline for startups to improve their businesses (Nalintippayawong et al., 2018).

The authors postulated that IPS could also be used as determinants of volatility which is an important variable in a non-traditional valuation method such as a real option method. With the right application of the real option method, the investors as the buyer of the option does not have to be always right, as they would only lose small portions of his capital (premium). The potential profit can even be maximized further by using certain strategic options such as buying call-and-put options at the same time (straddle or strangle strategies) or insurance strategy (covered call or protective put). This would entice investors to invest in risky assets such as startups by adopting such strategy options. Startup founders could also focus more on growing the company with the proper capital support from the investors.

Limitation and Further Research

There are some limitations in this study that warrant mentioning for the improvement of future research. The scope could be expanded to cover different stages of digital startup (growth or mature) to assess its impact towards IPS. The same model could later be adopted in other potentially similar startup ecosystems in South East Asia.

To improve objectivity of the response, other types of respondents such as angel investors could be considered. The usage of panel data across multiple time series would improve the validity and reliability of the research. It is also interesting to find the correlation between nominal indicators (i.e. the existence of shareholder agreement or business license) and the

IPS value for each startup. The IPS will need to be back-tested by comparing with investment decisions during the actual fund-raising events in order to test the robustness of the model.

While there are still lot of debates around the usage of MDA for this kind of research, it might be worthwhile to compare the results by using other approaches such as Probit Analysis, Recursive Partitioning Algorithm, and Neural Networks (Siddiqui, 2012) to validate the result. Future research may also identify how IPS would act as a determinant factor towards the independent variable of valuation method such as volatility in real option.

The IPS model can be potentially be used as preliminary selection or necessary condition to select startups with a higher degree for investment prior to actual fund-raising events. It could later be combining with valuation method such as real option as sufficient condition to derive fair value for both investors and startup founders.

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