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Research Paper

Impact of Founder, Social Media, IPR, and Business Sector on Advanced-Stage Startup Funding in Indonesia

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Abstract

In recent years, there has been a significant increase in the growth of startups, particularly in developing nations. There are numerous opportunities for startups to innovate as a result of the rapid growth of technology, which can be utilized to better the lives of a great number of people in a variety of fields. Pioneering startups must place a significant emphasis on investment as it is a critical determinant in sustaining business growth and innovation. A multitude of organizations are compelled to cease operations and innovation as a result of insufficient financial resources. Often, venture capital (VC) firms or angel investors provide financial support to startups. Each year, a venture capitalist may assess thousands of funding proposals from startups. It signifies that venture capital entry is competitive for each startup. The many factors that influence a venture capitalist's decision to invest in a startup have been the subject of numerous studies. This study employs a multiple linear regression model to examine the influence of human capital, social media, the business sector, and entrepreneur gender on funding for advanced-stage startups in Indonesia.

Keywords: *Venture Capitals (VCs), Startup, Investment, Human Capital, Social Media, Intellectual Property Rights (IPRs), Business Sector, Founder Gender*

INTRODUCTION

Startups can't get off the ground or stay in business without adequate funding (Binowo & Hidayanto, 2023). A company's prospects, profitability, and ability to expand are all affected by the choices made early on regarding the distribution of capital, such as the ratio of debt to equity (Cassar, 2004). Startups' innovation efforts are influenced by the amount of investment (Lin, 2020; Yang & Tu, 2020).

There are two main sources of capital for startups: internal and external (Obraztsova et al., 2017). Obtaining capital from the founder's network of friends and family is an example of internal funding. When a company receives funds from places other than its own family or relatives, this is called "external funding." This could be from angel investors, banks, or VC companies.

The startup's early stages will be supported by the founders' funds. When starting a business, founders often look to relatives and friends for initial funding. Unfortunately, they can't keep their business running on exclusively their savings and the money from their families. Therefore, entrepreneurs might look for funding through many sources such as bank loans, loans for small and medium businesses, or even venture capital. The company can start looking for investors, usually angel investors or venture capital (VC), after the product or service has a clear path and physical form, such as being operational or at least at the prototype stage. This is called external funding.

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According to Welter et al. (2023), venture capitalists are vital to the success and continued existence of numerous organizations. Another idea is crowdfunding, which is when a large number of people with an interest in a project or business pool their money to help support its development (Ren et al., 2020).

Furthermore, new company startups are often eligible for financial assistance from the government. A total of 1,190 startups may be found across Indonesia, according to data collected by the Indonesia Digital Creative Industry Society (MIKTI) in 2021. Therefore, it becomes difficult for the government to provide funding to each startup. The lack of adequate funding is a common top concern among Indonesian companies, according to MIKTI (2021). This highlights how a major and frequently faced challenge for entrepreneurs in Indonesia is the matter of startup funding.

Due to the significant level of uncertainty surrounding startups, investors often struggle to choose where to best allocate their funds. In the early phases of their startup, many entrepreneurs encounter challenges when trying to secure funding. Funding for early-stage businesses can thus be more easily secured by founders with extensive professional networks (Alexy et al., 2010; Shetty & Sundaram, 2019).

Because of that, it is critical to understand the factors associated with startup funding. Additionally, startups are vital to the economy and innovation of an entire nation (Nigam et al., 2021). Based on their developmental stage, newly founded startup differs in character from older enterprises (Shetty & Sundaram, 2019). Having a basic knowledge of the factors that can affect startup funding is essential for entrepreneurs and investors, especially when they are in the early stages. Very little academic work has focused on the factors that influence the procurement of capital for startups at the institutional level. Additionally, to maintain their momentum and push additional innovation, advanced-stage startups also need financial backup.

In previous research, it was found that the founder's education from a well-known university (Nigam et al., 2020; Nigam et al., 2021) and the number of followers on social media (Jin et al., 2017; Nigam et al., 2020) were signals for a startup to obtain better funding. Apart from that, it was also found that certain business sectors had a significant effect on reducing startups' chances of obtaining funding (Nigam et al., 2021). This is because business sectors that are unusual or even disruptive still require a lot of effort to gain profits. On the other hand, there is a tendency for there to be a bias towards female founders in obtaining funding(Färber & Klein, 2021). Several other studies have also tried to find out the impact that IPR has on startup funding. However, there has been no research that specifically compares the impact that the founder's educational history, business sector, founder gender and IPR have on the funding obtained by startups (Chen et al., 2018; Fischer & Ringler, 2014; Hochberg et al., 2018). Apart from that, there is still little research that can provide empirical evidence of the impact of startup funding, especially on advanced-stage startups.

This research is divided into five chapters. The first chapter is an introduction. In the second chapter, the literature review of previous research is discussed. Meanwhile, the third and fourth chapters respectively discuss the methodology used and the results obtained in this research. The fifth chapter discusses conclusions along with limitations and ideas for the future development of this research.

LITERATURE REVIEW

According to Acs & Audretsch (1988) and Cumming et al. (2014), startups play a pivotal role in stimulating innovation and accelerating economic advancement inside a nation. Startups are also vital to creating jobs and boosting productivity. Accordingly, numerous governments enact measures to facilitate their launch and growth (Melcangi & Turen, 2023). The startup life cycle consists of three stages: formation or pioneering, validation (which includes sales), and expansion or growth (which focuses on scaling) (Binowo & Hidayanto, 2023).

Researchers argue that having access to capital is crucial for successful startup management (Aidis, 2005; Beck et al., 2008; Colombo & Grilli, 2007; Kuntchev et al., 2013; Obraztsova et al., 2017). However, many startups fail because of several reasons. According to Gompers & Lerner (2002) and Lane et al. (2017), over ninety percent of businesses encounter problems and eventually fail during their early or pioneering stages.

According to the U.S. Bureau of Labor Statistics, As many as 23.2% of American startups fail within their first year of operation in 2023. Nearly half of the startups (47%) had trouble getting funding or attracting investors, and also 44% had their money run out. When it comes to American startups, just 52% make it to year five.

But, in contrast to developed nations like the US, the startup failure rate in developing nations is far greater. Ninety to ninety-five percent of Indian startups fail within the first five years, as reported by Nigam et al. (2020). Capital contributes to 34.1% of Indonesia's startup concerns, according to data from the Indonesia Digital Creative Industry Society (MIKTI) in 2021. Furthermore, about the potential improvement in the availability of funding within Indonesia's startup ecosystem, 24.4% of startups have expressed hope. Investors must exercise extreme caution when selecting which startups to back financially due to the high failure rate and risk associated with new enterprises.

The capacity to detect and seize opportunities is a needed quality of an entrepreneur. They will start by making do with what they have on hand, solving local issues, or depending on their ideas. Yet, they will surely seek outside help to plan and carry out the creation of any kind of output (Baraldi et al., 2019).

The founders will have a lot of knowledge about the startup's prospects and growth because of their greater involvement with the company. On the other hand, outside investors usually know a lot about marketing and business trends. Founders and investors could end up with different perspectives due to a lack of shared knowledge (Gompers & Lerner, 2002). Despite investors and entrepreneurs having unequal access to information, signaling theory can help level up the information (Connelly et al., 2011).

According to several studies, human capital—which includes factors like education and work experience—has a major impact on the funding of startups. Additional research argues that social media platforms like Facebook, Twitter or X, and LinkedIn can be good indicators for investors. Additionally, further research emphasizes the value of copyrights and patents as a sign of creativity and a possible protection for business owners.

Founder’s human capital

The combination of an individual's competence, expertise, and experience is called human capital (Singh et al., 2019). When there is a mismatch in knowledge between founders and outside investors, the latter looks to the former's human capital to determine whether and how much to invest in a startup (Honjo et al., 2022; Ko & McKelvie, 2018). Among other factors, the make-up of the founding team is a crucial component for a digital startup's survival during the pioneering stage (Binowo & Hidayanto, 2023).

If there are no records of past performance, the human capital levels of the founders should be used as an indicator of the quality of their businesses Ko & McKelvie, 2018). Human capital subjects are those who have completed formal education and have work experience. Apart from that, entrepreneurs' pre-entry skills impact their early-stage success (Baptista et al., 2014).

Several researchers have found that the educational background of a startup's founders is a strong predictor of the startup's success (Honjo et al., 2022; McCarthy et al., 2023; Noviantoro et al., 2020; Thanapongporn et al., 2021) Both Shetty & Sundaram (2019) and Nigam et al. (2021) found that founders with degrees from well-known universities had a better chance of attracting investors. Most people agree that a degree from a reputable university is a good indicator of quality.

Entrepreneurial team members with extensive expertise and good education should steer a startup that is looking to raise substantial capital, according to Ko & McKelvie (2018). However, startups in India were able to secure finance regardless of the founder's educational background, according to research by Nigam et al. (2021). So, more study is necessary before concluding the impact of a startup's founder's educational background on funding.

Thus, the following is a summary of the theory based on prior research:
Hypothesis 1 : Startups in Indonesia with founders who have degrees from highly esteemed local and international colleges tend to receive more series funding.

Acquiring practical experience, in addition to formal education, is one way to increase human capital. Tacit or non-explicit knowledge can be accessed through work experiences (Singh et al., 2019) When a company's founder has solid job experience, investors are more likely to finance the venture. (Colombo et al., 2004; Colombo & Grilli, 2010).

In addition, founders in the same field can benefit from discovering more about the market and the technologies that are already in use through their connections with other professionals in the field, who can lend a hand to their enterprise. Helfat & Lieberman (2002) also note that they already know the suppliers, customers, and other interested parties. According to Bosma et al. (2004), they are thought to have a greater understanding of the challenges encountered in this field, such as customer needs, products, and the required technology. The founder's expertise in technology, management, and the industry may be an indicator of the startup's long-term viability and growth potential (Delmar & Shane, 2006).

According to (Ko & McKelvie, 2018), investors at the seed stage of a firm's funding process place a high value on the founder's track record as a previous company founder. There is a common belief that a founder with prior business ownership experience is more equipped to handle the technical and managerial aspects of running a startup, as well as to spot and seize any opportunities that may arise (Delmar & Shane, 2006; McGrath & MacMillan, 2000).

Thus, the following is a summary of the theory based on prior research:
Hypothesis 2a : Series funding is more readily available to Indonesian startup founders with prior experience as a founder of a working company.
Hypothesis 2b : Series funding is more readily available to Indonesian startup founders with prior expertise in the same industry.
Hypothesis 3 : Higher working experiences are a signal for a higher series of funding.

Social media

In the digital age, social media has an essential effect on society (Amedie, 2015). According to (Goh et al., 2013), social media is a potent instrument that can improve product and service marketing. To evaluate the value of startups, social media activity can serve as a useful resource for investors, especially those without connections to the initial investors (Jin et al., 2017). Several studies have found that the amount of funding a business obtains is directly related to the size of its social media following (Banerji & Reimer, 2019; Jin et al., 2017; Nigam et al., 2020).

In addition, recent research shows that entrepreneurs who use LinkedIn well may be able to get investors more quickly in the next few years (Gloor et al., 2020). The following hypothesis can be

developed from various studies concerning the correlation between social media followers and startup funding:
Hypothesis 4a : Series funding is more likely to go to Indonesian startups with larger Facebook account followers.
Hypothesis 4b : Series funding is more likely to go to Indonesian startups with larger Twitter or X account followers.
Hypothesis 4c : Series funding is more likely to go to Indonesian startups with larger LinkedIn account followers.

Intellectual Property Rights (IPR)

De Leon et al. (2017) and Moroni et al. (2018) both acknowledge that innovation is critical to a country's economic and corporate progress. Moroni et al. (2018) state that a startup's growth and innovation must be continuous processes. All businesses must have legal protection for their innovative ideas (Baran & Zhumabaeva, 2018). To protect intellectual property (IP), it is necessary to register the results of research and development. Protecting one's intellectual property (IP) is crucial for new businesses, particularly in their early stages (De Leon et al., 2017).

Several studies state that intellectual property rights (IPR) can be utilized as collateral to acquire funding if a firm does not have any tangible assets to use as insurance (Fischer & Ringler, 2014; Gredel et al., 2012; Hochberg et al., 2018) One measure of how serious companies are about protecting their ideas is the number of intellectual property rights (IPRs) they have (Baran & Zhumabaeva, 2018). An indication of a startup's commitment to safeguarding R&D results is the extent to which it owns intellectual property rights (IPRs).

Nevertheless, according to Graham & Sichelman (2016), intellectual property rights (IPR) are only useful in addition to other elements, such as human and social capital, to entice investors. According to Indonesia's Directorate General of Intellectual Property Rights (IPR), startups often have four types of IPR: brand, patent, copyright, and industrial design.

Brand rights include the ability to use pictures, logos, and text to differentiate a company's goods and services from those of other companies. Protecting a company's name and emblem is what brand rights are all about. Inventors are recognized for their technological inventions through patent rights, which are exclusive privileges. Copyright is a privilege that people have under the law that can protect things like computer programs, literary works, and scientific discoveries. The creative economy of a country often uses copyright as a kind of protection. Designs used in manufactured items, products, industrial commodities, or crafts are protected by industrial design rights.

Therefore, the following hypothesis requires more investigation into the effect of IPRs on startup funding:
Hypothesis 5a : Series funding is more likely to go to Indonesian startups which has a brand right.
Hypothesis 5b : Series funding is more likely to go to Indonesian startups which has a patent right.
Hypothesis 5c : Series funding is more likely to go to Indonesian startups that have an industrial design right.
Hypothesis 5d : Series funding is more likely to go to Indonesian startups which has a copyright.

Business model

The ability of entrepreneurs to successfully overcome the pioneering phase of the digital startup is heavily dependent on business models and the challenges faced by startups, according to qualitative research by Binowo & Hidayanto (2023). Emir Hidayat et al. (2022) noted that several business models, including e-commerce and big data, benefit from the availability of short-term capital. Contrarily, a variety of still-rare or even disruptive company models can have a detrimental effect on funding (Nigam et al., 2021). This is because breaking into new markets sometimes necessitates extensive R&D efforts from disruptive business models. This causes some investors to be wary about short-term investments in these firms.

Therefore, the following hypothesis requires more investigation into the effect of the business model on startup funding:
Hypothesis 6a : Series funding is more likely to go to Indonesian startups operating in the financial sector.
Hypothesis 6b : Series funding is more likely to go to Indonesian startups operating in the logistics sector.
Hypothesis 6c : Series funding is more likely to go to Indonesian startups operating in the consumer sector.
Hypothesis 6d : Series funding is more likely to go to Indonesian startups operating in the education technology sector.

Founder gender
According to (Nigam et al., 2020), men make up 92% of India's startup founders. Also, female-led businesses are still in the minority and often get less investment than their male-only founders, according to several recent studies (Färber & Klein, 2021; Zhang et al., 2020).
Hypothesis 7 : Series funding is more likely to go to Indonesian startups with all founders gender being male.

METHODOLOGY

Data collection

This research undertakes a comprehensive and systematic approach to understand the landscape of startup funding in Indonesia, focusing on entities that have received at least Series A funding. The study encompasses a broad sample size of 135 startups, ensuring a robust and representative dataset for analysis. Data collection is meticulously conducted through a variety of sources to ensure depth and reliability. Primary sources include established online databases such as Crunchbase and Tracxn, which are renowned for their extensive records on startup activities and funding rounds. In addition to these, the research employs targeted Internet searches using specific, well-crafted keyword queries to uncover relevant data that may not be captured in the main databases.

The scope of data collection is extensive and includes various critical dimensions. Key among these is the educational background of the founders, which is scrutinized to understand if and how formal education influences funding success. This aspect delves into the specifics of the degrees obtained, the fields of study, and the institutions attended, offering a nuanced view of the educational landscape among successful startup founders.

Furthermore, the research probes into the founders' professional experiences, aiming to draw correlations between their career histories and their startups' funding achievements. This includes analyzing their previous roles, the nature and size of organizations they've worked in, and their industry relevance and expertise. Such information is pivotal in assessing the impact of professional networks, industry insights, and managerial competencies on securing funding.

Additionally, a significant focus is placed on the startups' digital footprint, specifically their social media presence. The study methodically collects and evaluates data from prominent social platforms like Facebook, LinkedIn, Twitter, or X (a stand-in for any other relevant platform), considering factors such as follower count, engagement rates, and content strategy. This analysis aims to gauge the influence of social media visibility and engagement on attracting investors and securing funding.

Data collection for this comprehensive study is projected to continue until April 2023, allowing for a dynamic and up-to-date dataset. This timeframe enables the capture of the most recent funding rounds and developments, ensuring the study's findings are relevant and reflective of the current market and investment trends. The approach is designed to produce a multifaceted and in-depth understanding of the factors influencing startup funding in Indonesia, providing valuable insights for founders, investors, and policymakers.

Dependent variable
To test the impact that factors in previous research have on startup funding, we use the series of funding (Series_Funding) as the dependent variable. We collect information regarding the series of startup funding, with a minimum limit that startups must obtain funding no later than April 2018. This limitation is done so that we can find out the latest factors that influence startup funding in Indonesia. However, because the series has a fixed amount, coding needs to be done, with the A series being given a quantity of 1, the B series being given a quantity of 2, the C series being given a quantity of 3, and the D series or above being given a quantity of 4.

Independent variables
Human Capital
We believe that founder human capital plays an important role in startup funding. Human capital factors are divided into two parts, namely education and work experience. We use the top education variable (Top_Edu) which acts as a dummy variable if there is a founder who completed his education at the best campus in Indonesia or globally. Apart from that, we also use the prior founder (Prior_Founder) and prior related field (Prior_Related) variables, each of which is a dummy variable for startups that have at least one founder who has experience as a founder in a previous company and has worked in a company operating in the same field as the startup he is building. The final variable related to human capital is the average founder experience (AvgFounder_Exp) which is a continuous variable. We argue that the more experience a founder has, the greater the startup's chances of obtaining greater funding.

Social media
We included three social media variables, namely Facebook, Twitter, and LinkedIn. Due to the large distribution of data on social media, we carried out a natural logarithmic transformation of these three variables into Ln (FB), Ln (Twitter), and Ln (LinkedIn). This transformation is carried out to obtain smoother data distribution. These three variables are continuous.

Intellectual Property Rights (IPR)
In the IPR factor, we use four variables, each of which is a type of IPR that a startup can have, there are brand (Brand), patent (Patent), industrial design (ID), and copyright (Copyright). These four variables are dummy variables that show the ownership of the type of IPR of each startup.

Control variables
Business model
In the business model variable, we use four variables which are the top four business sectors in the data we collected, namely financial (Sec_Financial), logistics (Sec_Logistic), consumer (Sec_Consumer), and education technology (Sec_Edtech). These four variables are dummy variables.

Founder gender

To test the impact of male gender, we use a dummy variable for the variable (All_Male) with a value of 1 for startups whose founders are all male.

Calculation

There are six multiple linear regression models presented here to test the primary empirical hypotheses from the literature. The first step is to build a regression model using the previously mentioned independent and control variables to forecast the series funding (Series_Funding). All of the independent and control variables examined had variance inflation factors (VIFs) below the 5 threshold and tolerance levels above the 0.2 threshold, according to post hoc multicollinearity diagnostics. To test for the predicted signal, we used a multiple regression model (Model 1) based on the potential components that could explain the series of funding for startups in Indonesia.

$$\begin{aligned} Series\_Funding_i = \; & \beta_0 + \beta_1 \, Top\_Edu_i + \beta_2 \, PriorFounder\_Exp_i + \\ & \beta_3 \, PriorRelated\_Exp + \beta_4 \, AvgFounder\_Exp_i + \\ & \beta_5 \, Ln\,(FB)_i + \beta_6 \, Ln\,(Twitter)_i + \\ & \beta_7 \, Ln\,(LinkedIn)_i + \beta_8 \, Brand_i + \beta_9 \, Patent_i + \\ & \beta_{10} \, ID_i + \beta_{11} \, Copyright_i + \\ & \beta_{12} \, Sec\_Financial_i + \beta_{13} \, Sec\_Logistics_i + \\ & \beta_{14} \, Sec\_Consumer_i + \beta_{15} \, Sec\_EdTech_i + \\ & \beta_{16} \, All\_Male_i + \varepsilon_i \end{aligned} \tag{1}$$

In the first model, we include all of our independent and control variables. We also conducted five more models to understand how far the contributions of the different variables are. Model 2 does not include Facebook in the analyses; Model 3 does not include LinkedIn; Model 4 does not include Twitter or X; Model 5 does not include any variables about social media; and 6 does not include copyright. We can see if any of these factors could hide the other variables' true impact in the initial model.

FINDINGS AND DISCUSSION

Findings

Table 1 and Table 2 show the bivariate correlation between all the variables involved, both dependent and explanatory variables. We can see that there is a correlation between the dependent variable and the explanatory variables, namely Ln (FB), Ln (Twitter), Ln (LinkedIn), and Copyright, with all variables having a strong correlation (>0.3) except the Copyright variable.

Table 1. Nonparametric correlations– Kendall's tau_b part 1

	Variables	1	2	3	4	5	6	7
1	Series_Funding	1.000						
2	Top_Edu	0.088	1.000					
3	PriorFounder_Exp	-0.041	0.012	1.000				
4	PriorRelated_Exp	-0.119	-0.041	0.120	1.000			
5	AvgFounder_Exp	-0.055	-0.030	.198**	.233**	1.000		
6	Ln (FB)	.493**	.171*	-0.024	-.163*	-.131*	1.000	
7	Ln (Twitter)	.396**	.186**	-0.005	-.147*	-.136*	.461**	1.000
8	Ln (LinkedIn)	.438**	0.105	-0.060	-0.115	-.145*	.344**	.358**
9	Brand	0.051	-0.070	-0.114	-0.107	-0.125	0.044	0.053
10	Patent	0.110	0.068	0.112	-0.077	-0.114	0.081	0.103

11	Industrial Design	0.080	0.035	-0.006	-.222*	-.211**	0.117	0.115
12	Copyright	.216**	0.000	0.044	-0.133	-0.098	0.089	.202**
13	Sec_Financial	0.133	-0.026	-.311**	0.000	0.078	0.082	0.123

14	Sec_Logistics	-0.073	0.009	0.073	0.000	0.072	-0.081	-.155*
15	Sec_Consumer	0.094	-0.049	0.044	0.090	-0.052	0.092	-0.070
16	Sec_EdTech	-0.064	0.117	.189*	-0.022	-0.012	0.017	.174*
17	All_Male	-0.020	0.069	-0.009	-0.050	-0.002	-0.009	-0.023

Table 2. Nonparametric correlations– Kendall's tau_b part 2

	8	9	10	11	12	13	14	15	16	17
8	1.000									
9	0.079	1.000								
10	0.070	0.045	1.000							
11	0.128	0.038	.499**	1.000						
12	0.079	-0.107	0.134	0.155	1.000					
13	0.037	0.091	-0.057	-0.151	-.213*	1.000				
14	0.126	-0.129	0.002	0.032	-0.055	-.188*	1.000			
15	0.049	-0.047	-0.152	-0.051	0.026	-.308**	-0.160	1.000		
16	0.007	0.038	-0.075	-0.063	0.089	-0.151	-0.078	-0.128	1.000	
17	-0.053	-0.082	0.034	-0.012	0.050	0.050	0.109	-0.155	0.137	1.000

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Table 3 shows the Variance Inflation Factor (VIF) and Tolerance values which are multicollinearity tests. We can see that the largest VIF value of all the variables tested in all models is 2,248, which is still below the multicollinearity limit of 5. We can see that the lowest tolerance value of all the variables tested in all models is 0.429, which is still above the multicollinearity limit of 0.2. This means that in all the models we use, there is no multicollinearity.

Table 3. Variance Inflation Factor (VIF)

Model	1		2		3		4		5		6	
	Collinearity Statistics		Collinearity Statistics		Collinearity Statistics		Collinearity Statistics		Collinearity Statistics		Collinearity Statistics	
	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
Top_Edu	0.904	1.107	0.918	1.089	0.904	1.107	0.912	1.097	0.968	1.033	0.912	1.096
PriorFounder_Exp	0.783	1.277	0.784	1.276	0.785	1.274	0.786	1.272	0.789	1.268	0.785	1.274
PriorRelated_Exp	0.844	1.185	0.860	1.163	0.844	1.185	0.844	1.185	0.867	1.154	0.850	1.177
AvgFounder_Exp	0.770	1.299	0.770	1.299	0.775	1.290	0.774	1.291	0.792	1.262	0.771	1.298
Ln (FB)	0.516	1.939			0.547	1.829	0.644	1.553			0.516	1.938
Ln (Twitter)	0.429	2.332	0.535	1.868	0.488	2.048					0.445	2.248
Ln (LinkedIn)	0.557	1.795	0.590	1.694			0.634	1.577			0.559	1.789
Brand	0.892	1.122	0.894	1.118	0.896	1.116	0.893	1.120	0.902	1.109	0.909	1.100
Patent	0.695	1.439	0.696	1.437	0.695	1.439	0.695	1.438	0.698	1.433	0.698	1.433
Industrial Design	0.669	1.494	0.669	1.494	0.674	1.485	0.670	1.494	0.677	1.478	0.670	1.493
Copyright	0.819	1.221	0.819	1.220	0.822	1.216	0.850	1.177	0.889	1.124		
Sec_Financial	0.625	1.599	0.626	1.598	0.628	1.592	0.639	1.565	0.674	1.484	0.667	1.498
Sec_Logistics	0.743	1.346	0.743	1.346	0.834	1.200	0.777	1.288	0.844	1.185	0.751	1.331
Sec_Consumer	0.712	1.404	0.730	1.369	0.728	1.374	0.727	1.376	0.758	1.319	0.713	1.402
Sec_EdTech	0.790	1.266	0.801	1.249	0.791	1.265	0.836	1.196	0.840	1.190	0.790	1.266
All_Male	0.922	1.085	0.925	1.081	0.924	1.083	0.928	1.078	0.933	1.072	0.927	1.079

Min	0.429	0.535	0.488	0.634	0.674	0.445
Max	2.332	1.868	2.048	1.577	1.484	2.248

Table 4. Summarize Multiple Linear Regression model 1 until model 3

	1				2				3			
	Unstandardized Coefficients		Standardized Coefficients	Sig.	Unstandardized Coefficients		Standardized Coefficients	Sig.	Unstandardized Coefficients		Standardized Coefficients	Sig.
	B	Std. Error	Beta		B	Std. Error	Beta		B	Std. Error	Beta	
(Constant)	-1.891**	0.710		0.009	-1.764*	0.760		0.022	-0.204	0.626		0.745
Top_Edu	-0.049	0.174	-0.018	0.781	0.046	0.185	0.017	0.805	-0.043	0.186	-0.016	0.818
PriorFounder_Exp	-0.038	0.149	-0.018	0.796	-0.021	0.159	-0.010	0.897	-0.068	0.158	-0.032	0.670
PriorRelated_Exp	-0.039	0.146	-0.018	0.791	-0.125	0.155	-0.058	0.421	-0.031	0.156	-0.015	0.842
AvgFounder_Exp	0.023	0.015	0.110	0.127	0.024	0.016	0.113	0.141	0.018	0.016	0.084	0.268
Ln (FB)	0.131***	0.031	0.374	0.000					0.162***	0.032	0.461	0.000
Ln (Twitter)	0.018	0.026	0.064	0.505	0.068**	0.025	0.247	0.008	0.056*	0.026	0.204	0.035
Ln (LinkedIn)	0.241***	0.057	0.353	0.000	0.299***	0.059	0.438	0.000				
Brand	0.011	0.454	0.002	0.981	0.114	0.486	0.017	0.815	0.141	0.484	0.021	0.771
Patent	0.290	0.277	0.078	0.298	0.326	0.297	0.088	0.274	0.295	0.296	0.080	0.322
Industrial Design	-0.206	0.327	-0.048	0.530	-0.234	0.350	-0.055	0.505	-0.096	0.348	-0.022	0.784
Copyright	0.295*	0.148	0.138	0.049	0.286^	0.159	0.133	0.074	0.332*	0.158	0.155	0.038
Sec_Financial	0.214	0.181	0.093	0.240	0.236	0.194	0.103	0.225	0.265	0.193	0.116	0.171
Sec_Logistics	-0.262	0.258	-0.074	0.312	-0.258	0.276	-0.073	0.351	0.096	0.260	0.027	0.713
Sec_Consumer	0.212	0.185	0.085	0.254	0.337^	0.195	0.135	0.088	0.324^	0.195	0.130	0.099
Sec_EdTech	-0.289	0.301	-0.068	0.339	-0.436	0.320	-0.102	0.176	-0.319	0.322	-0.074	0.323
All_Male	0.024	0.157	0.010	0.879	0.061	0.167	0.025	0.716	-0.004	0.167	-0.002	0.982

Table 5. Summarize Multiple Linear Regression model 4 until model 6

	4				5				6			
	Unstandardized Coefficients		Standardized Coefficients	Sig.	Unstandardized Coefficients		Standardized Coefficients	Sig.	Unstandardized Coefficients		Standardized Coefficients	Sig.
	B	Std. Error	Beta		B	Std. Error	Beta		B	Std. Error	Beta	
(Constant)	-1.998**	0.691		0.005	0.936	0.749		0.214	-1.728*	0.714		0.017
Top_Edu	-0.038	0.173	-0.014	0.828	0.341	0.222	0.129	0.127	-0.083	0.175	-0.031	0.638
PriorFounder_Exp	-0.033	0.148	-0.016	0.825	0.012	0.195	0.005	0.953	-0.052	0.150	-0.025	0.730
PriorRelated_Exp	-0.038	0.146	-0.018	0.794	-0.223	0.190	-0.104	0.242	-0.064	0.147	-0.030	0.667
AvgFounder_Exp	0.022	0.015	0.106	0.138	0.002	0.019	0.012	0.900	0.024	0.015	0.114	0.116
Ln (FB)	0.140***	0.027	0.400	0.000					0.130***	0.031	0.372	0.000
Ln (Twitter)									0.027	0.026	0.100	0.295
Ln (LinkedIn)	0.254***	0.053	0.372	0.000					0.247***	0.058	0.362	0.000
Brand	0.000	0.453	0.000	0.999	0.434	0.595	0.063	0.467	-0.115	0.455	-0.017	0.801
Patent	0.294	0.276	0.079	0.290	0.440	0.365	0.119	0.229	0.325	0.280	0.088	0.248
Industrial Design	-0.201	0.326	-0.047	0.540	0.053	0.429	0.012	0.901	-0.189	0.331	-0.044	0.569
Copyright	0.314*	0.145	0.146	0.033	0.603**	0.187	0.281	0.002				
Sec_Financial	0.231	0.178	0.101	0.197	0.621**	0.230	0.271	0.008	0.123	0.177	0.054	0.489
Sec_Logistics	-0.297	0.252	-0.084	0.239	0.107	0.319	0.030	0.737	-0.315	0.259	-0.089	0.227
Sec_Consumer	0.194	0.182	0.078	0.289	0.552*	0.236	0.221	0.021	0.198	0.187	0.079	0.292
Sec_EdTech	-0.242	0.292	-0.056	0.409	-0.098	0.385	-0.023	0.800	-0.290	0.305	-0.068	0.344

All_Male	0.016	0.156	0.006	0.920	-0.057	0.205	-0.024	0.783	0.046	0.158	0.019	0.773

*** p< .001. ** p< .01. * p< .05. ^ p<.0.10.

Table 4 and Table 5 contain a summary of our regression analysis, with Table 6 containing the F-statistic and sig., R^2, and adjusted R^2 values. A very significant F-statistic value was obtained at the 1% level for all models, except model 5, where the significance obtained was 10%, meaning that the null hypothesis was rejected for all models, or in other words, some variables influenced the dependent variable.

From the first model, we found that the variables Ln (FB) and Ln (LinkedIn) had a very significant influence on the model and Copyright had a quite significant influence. Meanwhile, in models 2 and 3, respectively, when the variables Ln (FB) and Ln (LinkedIn) are removed from the basic model, the variables Ln (Twitter) and Sec_Consumer enter as significant variables which replace the impact of the variables removed from the model used. Meanwhile, in model 4, there was a very significant decrease in model fit and in other words, all variables related to social media had a very significant influence on the model we used.

Table 5. F-statistics and significance, R^2, and adjusted R^2 from all model

	1	2	3	4	5	6
F	8.609	6.935	7.016	9.196	2.015	8.701
F>Prob	0.000	0.000	0.000	0.000	0.025	0.000
R2	0.539	0.466	0.469	0.537	0.178	0.523
Adj R2	0.476	0.399	0.402	0.478	0.09	0.463

In the adjusted R^2 value, we find that our fourth model is slightly better than the first model (0.478>0.476). If we look at Table 1, we can see that variables related to social media do have a significant and strong correlation with the dependent variable, but we also find that these variables related to social media are correlated with each other. This means that if we ignore the Twitter variable in the basic model, we can get a slightly better model. However, if we cannot have information regarding the startup's Facebook or LinkedIn account, we can use the startup's Twitter account information as a good substitute for our model.

Discussion

In this research, we found that all human capital factors did not have a significant impact on the model used. In other words, the human capital factor does not have a significant impact on startup funding at an advanced stage. In addition, our research did not find sufficient evidence that there is founder gender bias in advanced-stage startup funding in Indonesia.

In contrast, we found that social media factors play the most important role in advanced startup funding. Even though Twitter does not have an impact as significant as Facebook and LinkedIn, Twitter can act as a substitute for Facebook and LinkedIn if these two factors cannot be found. We also found that consumer and financial businesses tend to obtain a little bit better funding compared to other business models.

We also found that most of the IPR variables do not have a significant impact on advanced-stage startup funding in Indonesia, except for copyright. Even though copyright is not as significant as the social media variable, the copyright variable has quite an impact on advanced startup funding in Indonesia.

In this research, our findings are inversely proportional to findings in India(Nigam et al., 2020, 2021), where founder education plays an important role in startup funding. This may be due to the selection of the dependent variable in the form of a series of funding. Our findings are proof that founder education from a well-known university has no impact on advanced-stage startup funding. However, our findings are also in line with research in India where social media plays an important role in startup funding. Apart from that, we also agree on the importance of determining the business sector so that it has greater opportunities to obtain funding. Our research provides novelty in the form of adding the IPR factor to startup funding.

CONCLUSION

This research delves deeply into understanding the dynamics and determinants of advanced startup funding in Indonesia, aiming to identify the multifaceted factors that significantly influence the ability of startups to secure financial backing. Our comprehensive analysis has revealed several critical insights. Firstly, the study found that a startup's digital presence, particularly the number of followers on social media platforms like Facebook and LinkedIn, plays a crucial role in attracting funding. A robust following on these platforms is strongly associated with increased funding opportunities, indicating the importance of digital visibility and community engagement in the startup ecosystem.

Further, the research highlights the substantial impact of intellectual property ownership on funding prospects. Startups possessing copyrights demonstrated a markedly higher potential to secure more substantial funding amounts compared to their counterparts without such protections. This finding underscores the value of intellectual property as an asset and its role in enhancing a startup's appeal to investors. Interestingly, while a Twitter account didn't show a significant influence in the basic model, it emerged as a valuable asset when a startup's Facebook or LinkedIn accounts aren't performing optimally. This suggests that Twitter can serve as an effective alternative or supplementary channel for maintaining online engagement and visibility, which are crucial for funding. Moreover, the study also explores sector-specific trends within the Indonesian startup landscape. It was observed that startups operating in the consumer sector tend to secure better funding compared to those in other sectors. This indicates a possibly higher investor confidence in consumer-focused startups, reflecting market demand and the potential for growth and profitability in this sector.

LIMITATION AND FURTHER RESEARCH

Our research possesses several limitations that need recognition. In the first place, we examined in this study several determinants of startup funding, including human capital, social media, and IPR ownership, as well as several additional factors, including the industry and the gender of the founder. This research can additionally offer insights for entrepreneurs, including the significance of establishing publicly recognizable social media accounts for their ventures. While the model we employ is admirable, it is crucial to keep in mind that investors will undoubtedly take into account various other factors, including income, market size, sales of products or services, and so forth, when formulating their actual investment decisions. Furthermore, it is worth noting that the scope of this study is limited to funding for advanced-stage startups. Consequently, the non-influential or influential factors identified in this research may differ when applied to early-stage startups. Furthermore, it should be noted that this study was executed utilizing data from advanced-stage startups in Indonesia. Consequently, applying the findings to other regions could produce different outcomes, necessitating additional validation with data from other developing nations. Fourth, the utilization of a quantitative methodology in this study severely restricts the provision of qualitative insights that could elucidate the reasons behind the potential influence of these factors on startup funding. In conclusion, the databases we utilize—including Tracxn, Crunchbase, Facebook, Twitter/X, LinkedIn, and the websites of the Directorate General of Intellectual Property, and the Ministry of Law and Human Rights—are very limited in their ability to verify the validity and authenticity of the information we obtain.

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