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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 rapid technological growth, which can be used to improve the lives of many people across a variety of fields. Pioneering startups must place significant emphasis on investment, as it is a critical determinant of sustained business growth and innovation. A multitude of organizations are compelled to cease operations and innovation due to 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 cannot 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 early decisions about capital allocation, such as the debt-to-equity ratio (Cassar, 2004). Startups' innovation efforts are influenced by investment levels (Lin, 2020; Yang & Tu, 2020).

There are two primary 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 sources other than its family or relatives, this is referred to as "external funding." This could be from angel investors, banks, or VC companies.

The founders' funds will support the startup's early stages. When starting a business, founders often look to relatives and friends for initial funding. Unfortunately, they cannot keep their business running solely on their savings and family funds. Therefore, entrepreneurs might seek funding from various sources, such as bank loans, small- and medium-sized business loans, or 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. According to Welter et al. (2023), venture capitalists are vital to the success and continued existence of numerous organizations. Another idea is crowdfunding, in which a large number of people with an interest in a project or business pool their money to support its development (Ren et al., 2020).

Furthermore, new companies are often eligible for government financial assistance. A total of 1,190 startups were recorded across Indonesia in 2021, according to data collected by the Indonesia Digital Creative Industry Society (MIKTI). Therefore, it becomes difficult for the government to fund each startup. The lack of adequate funding is a common top concern among

Indonesian companies. This highlights how a major, frequently faced challenge for entrepreneurs in Indonesia is access to startup funding.

Due to significant uncertainty in the startup space, investors often struggle to decide where to allocate their funds. In the early stages of their startup, many entrepreneurs face challenges securing 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).

Accordingly, it is critical to understand the factors associated with startup funding. Additionally, startups are vital to a nation's economy and innovation (Nigam et al., 2021). Based on their developmental stage, newly founded startups differ in character from older enterprises (Shetty & Sundaram, 2019). A basic understanding of the factors that can affect startup funding is essential for entrepreneurs and investors, particularly in the early stages. Very little academic work has examined the factors that influence capital procurement for startups at the institutional level. Additionally, to maintain momentum and drive further innovation, advanced-stage startups require financial backing.

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. In addition, specific business sectors significantly reduced startups' chances of securing funding (Nigam et al., 2021). This is because sectors that are unusual or even disruptive still require significant effort to achieve profitability. On the other hand, there is a tendency for funding to be biased towards female founders (Färber & Klein, 2021). Several other studies have also sought to determine the impact of IPR on startup funding. However, no research has specifically examined the impact of the founder's educational history, business sector, founder gender, and IPR on the funding startups obtain (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, limitations, and ideas for future development of this research.

LITERATURE REVIEW

According to Acs and Audretsch (1988) and Cumming et al. (2014), startups play a pivotal role in stimulating innovation and accelerating economic advancement within 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, 23.2% of American startups failed in their first year of operation in 2023. Nearly half of the startups (47%) had trouble securing funding or attracting investors, and 44% ran out of money. When it comes to American startups, just 52% make it to year five.

However, 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, regarding potential improvements in funding availability within Indonesia's startup ecosystem, 24.4% of startups expressed optimism. Investors must exercise extreme caution when selecting which startups to back financially, given the high failure rate and the risks 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. However, 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 much 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 may hold different perspectives due to a lack of shared knowledge (Gompers & Lerner, 2002). Despite unequal access to information among investors and entrepreneurs, signaling theory can help level the information playing field (Connelly et al., 2011).

Several studies indicate that human capital—such as education and work experience—has a significant impact on startup funding. Additional research argues that social media platforms like Facebook, Twitter, X, and LinkedIn can be good indicators for investors. Additionally, further research emphasizes the value of copyrights and patents as indicators of creativity and potential protection for business owners.

Founder's Human Capital

The combination of an individual's competence, expertise, and experience is referred to as 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 composition of the founding team is crucial to a digital startup's survival during the pioneering stage (Binowo & Hidayanto, 2023).

If there are no records of past performance, the founders' human capital levels should serve 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 studies have found that the educational backgrounds of startup founders are strong predictors of startup success (Honjo et al., 2022; McCarthy et al., 2023; Suwarni et al., 2020; Thanapongporn et al., 2021). Both Shetty and Sundaram (2019) and Nigam et al. (2021) found that founders with degrees from well-known universities were more likely to attract investors. Most people agree that a degree from a reputable university is a good indicator of quality.

Entrepreneurial team members with extensive expertise and strong education should steer a startup seeking to raise substantial capital, according to Ko and McKelvie (2018). However, startups in India were able to secure financing regardless of the founders' educational backgrounds, according to research by Nigam et al. (2021). Further study is necessary before drawing conclusions about the impact of a startup 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 learning more about the market and existing technologies through their connections with other professionals in the field, who can assist their enterprise. Helfat and 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, including customer needs, products, and required technology. The founder's expertise in technology, management, and the industry may indicate the startup's long-term viability and growth potential (Delmar & Shane, 2006).

According to Ko and 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 prior company founder. There is a common belief that a founder with prior business ownership experience is better equipped to handle the technical and managerial aspects of running a startup, as well as to identify and seize 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 founders of working companies.
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 a significant impact on society (Amedie, 2015). According to Goh et al. (2013), social media is a potent tool that can improve product and service marketing. To evaluate the value of startups, social media activity can serve as a valuable 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 research and development results. 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 and Sichelman (2016), intellectual property rights (IPR) are only helpful when combined with 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 granted by law that can protect works such as computer programs, literary works, and scientific discoveries. The creative economy of a country often relies on copyright as a form 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 that have a brand right.
Hypothesis 5b: Series funding is more likely to go to Indonesian startups that have 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 that have a copyright.

Business Model

The ability of entrepreneurs to successfully navigate the pioneering phase of a digital startup is heavily dependent on the business model and the challenges startups face, according to qualitative research by Binowo and Hidayanto (2023). 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 entering new markets sometimes requires extensive R&D for 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 remain in the minority and often receive less investment than their male-only counterparts, 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' genders being male.

RESEARCH METHOD
Data collection

This research collected data from 135 startups in Indonesia that received at least series A funding. Data were collected from online databases and through random searches (Crunchbase, Tracxn, and Internet-based keyword searches). We also collect information such as founders' education, founders' work experience, and startups' social media accounts on Facebook, LinkedIn, Twitter, or X. Data collection will be carried out until April 2023.

Dependent variable

To test the impact of factors identified in prior research on startup funding, we use the series of funding (Series_Funding) as the dependent variable. We collect information on a series of startup funding rounds, with the minimum requirement that startups secure funding no later than April 2018. This limitation is to identify the latest factors influencing 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 is a dummy variable indicating whether a founder 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 average founder experience (AvgFounder_Exp), 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 extensive distribution of data on social media, we applied a natural logarithmic transformation to these three variables: Ln (FB), Ln (Twitter), and Ln (LinkedIn). This transformation is performed to obtain a smoother data distribution. These three variables are continuous.

Intellectual Property Rights (IPR)

In the IPR factor, we use four variables: brand (Brand), patent (Patent), industrial design (ID), and copyright (Copyright). These four variables are dummy variables indicating the type of IPR each startup owns.

Control variables

Business model

In the business model variable, we use four variables: the top four business sectors in the data we collected, namely financial (Sec_Financial), logistics (Sec_Logistics), 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 (All_Male) that equals 1 for startups with all-male founders.

Methodology

Six multiple linear regression models are 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 independent and control variables examined had variance inflation factors (VIFs) below the five threshold and tolerance levels above the 0.2 threshold, according to post hoc multicollinearity diagnostics. To test the predicted signal, we used a multiple regression model (Model 1) based on potential components that could explain the series of startup funding in Indonesia.

$$
\begin{aligned}
\text{Series\_Funding}_i \quad = \quad & \beta_0 + \beta_1 \, \text{Top\_Edu}_i + \beta_2 \, \text{PriorFounder\_Exp}_i + \\
& \beta_3 \, \text{PriorRelated\_Exp} + \beta_4 \, \text{AvgFounder\_Exp}_i + \\
& \beta_5 \, \text{Ln (FB)}_i + \beta_6 \, \text{Ln (Twitter)}_i + \\
& \beta_7 \, \text{Ln (LinkedIn)}_i + \beta_8 \, \text{Brand}_i + \beta_9 \, \text{Patent}_i + \\
& \beta_{10} \, \text{ID}_i + \beta_{11} \, \text{Copyright}_i + \\
& \beta_{12} \, \text{Sec\_Financial}_i + \beta_{13} \, \text{Sec\_Logistics}_i + \\
& \beta_{14} \, \text{Sec\_Consumer}_i + \beta_{15} \, \text{Sec\_EdTech}_i + \\
& \beta_{16} \, \text{All\_Male}_i + \varepsilon_i
\end{aligned}
\tag{1}
$$

In the first model, we include all of our independent and control variables. We also ran five additional models to understand how far the contributions of the different variables extend. 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 Model 6 does not include copyright. We can assess whether any of these factors could mask the effects of the other variables in the initial model.

FINDINGS AND DISCUSSION

Findings

Table 1 and Table 2 show the bivariate correlations among all variables, both dependent and explanatory. 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 except Copyright showing strong correlations (>0.3).

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 used to assess multicollinearity. We can see that the highest VIF value across all variables and models is 2,248, which is still below the multicollinearity threshold 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

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

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

From the first model, we found that the variables Ln (FB) and Ln (LinkedIn) had highly significant influences, and Copyright had a fairly significant influence. In models 2 and 3, respectively, when Ln (FB) and Ln (LinkedIn) are removed from the basic model, Ln (Twitter) and Sec_Consumer become significant and replace the effects of the variables removed. Meanwhile, in model 4, there was a very significant decrease in model fit, indicating that all variables related to social media had a very significant influence on the model.

Table 6. 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

From the adjusted R^2 values, we find that our fourth model is slightly better than the first (0.478 > 0.476). If we look at Table 1, we can see that variables related to social media show a strong, significant correlation with the dependent variable, but they are also 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 do not have information about the startup's Facebook or LinkedIn account, we can use the startup's Twitter account as a good substitute for our model.

Discussion

In this research, we found that none of the human capital factors had a significant impact on the model. In other words, the human capital factor does not have a significant impact on funding for advanced-stage startups. In addition, our research did not find sufficient evidence of 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 the same impact as Facebook and LinkedIn, it can serve as a substitute for either if those platforms are unavailable. We also found that consumer and financial businesses tend to secure better funding than 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. Although copyright is not as significant as the social media variable, it still has a significant impact on advanced startup funding in Indonesia.

In this research, our findings are inversely proportional to those in India (Nigam et al., 2020, 2021), where founder education plays an important role in startup funding. This may be due to selecting the dependent variable as 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 also align 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 to increase the likelihood of obtaining funding. Our research adds novelty by introducing the IPR factor into the startup funding landscape.

CONCLUSION

This research aims to find out the factors that influence advanced startup funding in Indonesia. Our findings found that the greater number of startup followers on Facebook and LinkedIn accounts had a very significant influence on startup funding. Startups with copyrights have a greater opportunity to secure funding than those without. Even though in the basic model a Twitter account does not have a significant influence, it can act as a substitute if one of the startup's Facebook or LinkedIn accounts is not running optimally. Apart from that, the consumer sector in Indonesia tends to have better funding than the other three sectors.

LIMITATION AND FURTHER RESEARCH

Our research has several limitations that need to be acknowledged. In the first place, we examined several determinants of startup funding in this study, including human capital, social media, and IPR ownership, as well as additional factors such as industry and founder gender. 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, product or service sales, and so forth, when formulating their 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, this study used 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 use of a quantitative methodology in this study severely limits the provision of qualitative insights that could elucidate 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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