

OVEROPTIMISM AND ENTREPRENEURIAL ECOSYSTEM: CITIES OF BOGOR AND DEPOK

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Abstract

Introducing innovative products and services by start-ups can positively influence a country's competitiveness. The environment represented by the entrepreneurial ecosystem (EE) stimulates entrepreneurship and influences founders' cognitive bias. Overoptimism has been studied as one of the main cognitive biases and found to be critical to new product development success (NPDS) or new venture performance (NVP). Nonetheless, studies on the EE influencing founders' overoptimism remain limited. This study aims to fill this gap by investigating the influence on overoptimism of the two most prominent EE domains based on the World Economic Forum's EE heatmap, namely the market and human capital domains. This study employs a questionnaire-based survey of 45 founders from digital start-ups in Bogor and Depok, Indonesia. The data is analyzed with partial least square structural equation modeling (PLS-SEM), finding that both EE domains significantly and positively influence overoptimism. In addition, the findings support previous studies by examining the influence of overoptimism on NPDS and NVP.

Keywords: Entrepreneurial ecosystem, overoptimism, new product development success, new venture performance.

Introduction

Isenberg (2010) observes Rwanda's considerable leap in per capita gross domestic product (GDP)—which has quadrupled since 1995—and the country's 'ease of doing business,' which has increased from being ranked 143rd to 67th globally. He argues that an environment supported by the government, private sector and non-profit organizations is a fertile ground for entrepreneurship, thus directly and indirectly supporting entrepreneurial activities in Rwanda. This environment is labeled as the entrepreneurial ecosystem (EE; Isenberg, 2010; Spigel, 2017). Isenberg (2011) proposes six domains with twelve components for analyzing EE, comprising finance, culture, support, human capital, markets, and policy. The World Economic Forum (2013) proposes eight pillars and their components, with heatmap (availability) information by region suggesting that the higher the percentage of respondents, the stronger the pillar in that region. Two out of eight pillars in the Asia region—to which Indonesia belongs—score higher than average (44%), namely 'human capital workforce' and 'accessible markets' (World Economic Forum, 2013). These two pillars belong to the market and human capital EE

domains (Isenberg, 2011; World Economic Forum, 2013).

A digital start-up is established by an individual or a collective of entrepreneurs or founders (Qoriawan & Apriliyanti, 2023). Successful founders typically acquire entrepreneurial skills and knowledge (human capital domain) and seize opportunities in the accessible market (markets domain) from EE (Khan *et al.*, 2021; Qoriawan & Apriliyanti, 2023). Khan *et al.* (2021) examined that self-confidence (internal factor), along with EE (external factor), exert a positive and significant impact on the performance of firms in the emerging economy of Pakistan. In other emerging economy, Colombia, South America, the success of creating an EE with technologically advanced public libraries, community centers, innovation centers and microfinance programs in Medellín city has created optimism (Isenberg, 2010). Confidence and optimism are examples of the cognitive biases (Thomas, 2018).

This study aims to examine the influence of the two aforementioned EE domains on the cognitive bias of founders—particularly overoptimism—in engaging in entrepreneurial activities and influencing firms' performance in the cities of Bogor and Depok. The two cities are selected be-

cause each has state-owned and private universities to develop a digital workforce, and they have a closer proximity to Jabodetabek (the urban agglomeration surrounding Jakarta), which contributes around 40% of the country's digital start-ups, or a total of 481 according to MIKTI (2021). The two cities have a total of 43 start-ups, accounting for approximately 10% of Jabodetabek's start-ups (MIKTI, 2021).

2021 and 2022 presented considerable obstacles for digital start-ups in Indonesia regarding investment, referred to as a funding winter (Singh & Goyal, 2024; Yusra, 2022). However, during the funding winter in 2022, one of the digital start-ups persistently developed relevant products for the target market to facilitate business growth and secure a further cycle of investor funding (Yusra, 2022). This condition raises the critical question whether there is a correlation between EE domains (markets domain) and the decision of founders (cognitive biases) to consistently develop products amid uncertainty to enhance firm performance and secure a further funding cycle. In decision-making, human judgment often leads to irrational choices among several alternatives, resulting in deviation or bias (Hilbert, 2012). His study asserted that cognitive decision-making bias, or cognitive bias, can be utilized to predict an individual's behavior. Cognitive biases, while capable of causing systematic errors and inferior results, play a crucial role in entrepreneurial decision-making (Thomas, 2018).

Thirteen distinct cognitive biases were discovered across the two studies from Zhang *et al.* (2020) and Thomas (2018). Overconfidence and overoptimism garnered the most attention, whilst the law of small numbers and the illusion of control attracted moderate attention (Thomas, 2018). According to Thomas (2018), there are three factors that influence cognitive biases. This study will examine one of the factors, environment and one of the main cognitive biases, overoptimism. The environment will be represented by EE. This study draws on EE theory to investigate which EE domains influencing the cognitive bias of the founders affect new product development success (NPDS) or new venture performance (NVP).

Start-ups possess significant potential to transform entire industries, stimulate innovation, attract further investments, increase competition, provide novel products and services, expand markets, and generate new employment opportunities (Mehmeti & Musabelli, 2024). Müller and Ram-

mer (2012) argue that start-ups introducing innovative products and services can positively influence national development and enhance competitiveness. Start-ups are categorized into four groups that contribute different impacts on economic growth and development (Müller & Rammer, 2012), whereby new technology- (or digital start-ups) and opportunity-based start-ups influence economic growth and development more than copycat start-ups and those driven by unemployment. Digital start-ups are newly established firms or ventures that leverage information technology to create products or services (Steininger, 2019).

Sandberg and Hofer (1987) identify three factors that influence new firm performance, namely the industry structure, firm strategy, and founding entrepreneur. New product development is a fundamental activity for firm competitiveness (McCann & Bahl, 2017) that forms the basis of the firm's strategy. Introducing new products constitutes a significant competitive maneuver for a company, and new product development represents a fundamental strategic decision (Smith *et al.*, 2001, cited by McCann & Bahl, 2017). Founding entrepreneur factors include founder traits, values, skills, experience, education, behavior, and decisions (Chrisman *et al.*, 1998). The founding entrepreneur's decision to devote attention to customers, products or services, resources, technology, and organization is the basis for pioneering a new company and significantly influences the firm's performance (Chrisman *et al.*, 1998). Hilbert (2012) argues that cognitive decision-making or cognitive biases can be used to predict the founding entrepreneur's decision-making. Hence, within the same industry, two factors influencing the firm's performance are the firm strategy—represented by new product development—and the founders, represented by the cognitive bias.

As one of the main cognitive biases that has been extensively examined, overoptimism reflects the belief that humans tend to overestimate the likelihood of positive events occurring, while disregarding the potential of unfavorable events beyond an individual's control (Zhang & Cueto, 2017). Examining the impact of overoptimism on the firm performance, Lowe and Ziedonis (2006) argue that in uncertain markets, entrepreneurs continue new product development through pivoting for a longer period than established companies, which is consistent with overoptimism in the

product development, while overoptimism influences the firm's performance through the economic returns obtained after an established company acquires the start-up.

This study holds relevance due to the increasing number of digital start-ups in Indonesia, representing a key emerging economy. However, research on the EE mostly focus on the developed economies (Qoriawan & Apriliyanti, 2023). Moreover, the research on EE predominantly relies on the geographic level output study economies (Qoriawan & Apriliyanti, 2023). The EE relevance on the emerging economies and its influence on the cognitive bias need further investigation.

Stam and Van de Ven (2021) use EE domains to measure the quality of EE in the cities of a developed country (the Netherlands) indicating the number of companies with high growth. Vedula and Kim (2019) use EE domains to measure the quality of EE in the metropolitan areas of another developed country (the United States) indicating the survival of the company. Leendertse *et al.* (2022) use EE domains to measure the entrepreneurial economies of EE in the European regions indicating the number of new companies in the area. Prior studies such as Qoriawan and Apriliyanti (2023) focus on the connections within the EE using a social network approach in Yogyakarta, while Msimango-Galawe and Majaja (2022) examine the key challenges and needs of entrepreneurs in Johannesburg analyzing the domains of EE. Chwolka and Raith (2023) and Rotondi (2024) examine overconfidence and market entry (markets domain) decision. Yang and Wang (2024) examine the influence of executives (human capital domain) on the individual overconfidence and the investment. Moreover, Thomas (2018) examines that studies on the influence of environment (EE) on cognitive biases (overoptimism) remains limited.

This study aims to fill the gap by examining the influence of two prominent EE domains (markets domain and human capital domain) in Indonesia (one of emerging economies) on one of cognitive main biases (overoptimism). Additionally, the study will investigate the impact of overoptimism on NPDS or NVP.

Entrepreneurial Ecosystem

Economic research consistently establishes a strong correlation between entrepreneurship and the quick generation of employment opportunities, the expansion of gross domestic product, and

the enhancement of long-term productivity (Isenberg, 2010). Feld (2012) highlights the significant impact of the EE on businesses and has become a pioneer in developing a regional ecosystem in Boulder City that contributes to the rapid growth of start-ups. Spigel (2017) examines the potential variations in EE configurations across two Canadian cities. However, despite their differences, the two EE configurations provide important benefits to new firms. The EE is defined as an amalgamation of social, political, economic, and cultural elements within a particular region that facilitates the development and growth of innovative start-ups while promoting the initiation, financing, and comprehensive support of high-risk ventures through encouraging new entrepreneurs and other stakeholders (Spigel, 2017).

The EE of Boulder City has developed in tandem with the rapid growth of start-ups (Feld, 2012). Feld (2012) initially observes that the EE of Boulder City is identified by many bootstrapped start-ups, and a strong inclination (bias) of founders to undertake tasks alone, due to the disconnect between founders and investors. This disconnect is also observed in the EE of Yogyakarta in Indonesia, based on the lack of a dense network and weak institutional policies (Qoriawan & Apriliyanti, 2023). The EE of Boulder City is progressing due to the strong connections and interactions between founders and investors that are being identified through the emergence of new VC firms, the formation of new start-ups, the acquisition of start-ups by public companies, and the IPO of start-ups (Feld, 2012). This study examines the condition of EE of the cities of Bogor and Depok, utilizing the domains of EE based on Isenberg (2011) and their availability in the region based on World Economic Forum (2013).

Following Isenberg (2011), the human capital domain involves considering two components and the market domain encompasses three components. Accordingly, human capital domain comprises the components of 'education and training' and 'workforce' (Isenberg, 2011; World Economic Forum, 2013). 'Education and training' in turn encompasses university education, pre-university education, technical, management or entrepreneurship training, and training through self-learning (De Winne & Sels 2010; Isenberg, 2011; Tabares *et al.*, 2015; World Economic Forum, 2013). The 'workforce' component encompasses personnel with managerial or technical proficiency, functional or specific skills, and experience (Fish & Srinivasan, 2012; Nicotra *et al.*,

2018; Leendertse *et al.*, 2022; World Economic Forum, 2013). Nicotra *et al.* (2018) propose that a research university is a component of the human capital domain, encompassing high-quality scientific research institutes and universities that contribute to the formation of spin-offs and technology transfer. However, in emerging economies, institutions and university academics' research and development capacities are comparatively inadequate, hindering research-driven innovation and standardization (Zoo *et al.*, 2017). Following Zoo *et al.* (2017), this study omits the research university component from the human capital domain.

The first component of the market domain is 'accessible markets,' which encompasses customers in both domestic and international marketplaces, specifically large corporations, small and medium-sized enterprises, and government entities (Isenberg, 2011; World Economic Forum, 2013). The second and third components belong to the networks of entrepreneurs or founders, comprising 'formal networks' and 'informal networks' (Cohen, 2006; Isenberg, 2011; Msimango-Galawe & Majaja, 2022). 'Formal networks' comprise the connections with financial institutions, academic institutions, governmental bodies, and major corporations, while 'informal networks' involve connections with family, friends, and peers (Birley, 1985; Neck *et al.*, 2004).

The creation and application of knowledge to develop new products and processes are at the center of attention in management concepts such as resource-based and dynamic capabilities theory (Varun Grover, 2001). The workforce is a crucial input for entrepreneurship, as it is closely related to the formation of new companies and start-up activities (Leendertse *et al.*, 2022). Apart from the positive relationship with entrepreneurial activity, entrepreneurs with a high level of general knowledge gained through education or previous entrepreneurial experience are more overoptimistic (Verheul & Carree, 2007). Hence, the following hypothesis is established:

H₁: Perceived ease of access to the human capital domain positively influences overoptimism.

Internet access and proficiency can empower smaller enterprises to adopt a more entrepreneurial approach to delivering products and services (Javalgi *et al.*, 2012). Moreover, according to Javalgi *et al.* (2012), products and services are transacted online to reach consumers in domestic and foreign markets, thereby expanding business opportunities. The authors also highlight that entrepreneurs become optimistic when they see the

market as an opportunity for expansion. Business actors can utilize social networks to obtain valuable information and expertise that supports entrepreneurship (Doh & Zolnik, 2011). Information, skills, and knowledge are transmitted to organizations that can utilize them most efficiently via social networks (Leendertse *et al.*, 2022). Hence, the following hypothesis is developed:

H₂: Perceived ease of access to the markets domain positively influences overoptimism.

Overoptimism

The emergence of bias in entrepreneurship arises from entrepreneurs' engagement in decision-making under risky conditions, including the limited cognitive capacity to process and retain information from complex scenarios, exposure to novel and unpredictable circumstances, a lack of access to historical trends and performance data, and insufficient time to capitalize on opportunities, all of which exacerbate uncertainty (Keh *et al.*, 2002). Cognitive biases elucidate the decision-making process involved in entrepreneurship, the conduct of entrepreneurs, firm success, and the distinctions between entrepreneurs and non-entrepreneurs (Thomas, 2018).

The two studies by Zhang *et al.* (2020) and Thomas (2018) discovered thirteen distinct cognitive biases. Overconfidence and overoptimism garnered the most attention, while the law of small numbers and the illusion of control attracted moderate attention (Thomas, 2018). Both have the character of being very optimistic, although overconfidence involves looking inward, while overoptimism involves considering the risk environment (Schade & Koellinger, 2007). This study specifically examines overoptimism.

Optimism and pessimism bias exert an immediate impact on individuals' emotional responses when confronted with challenges, encompassing a spectrum from enthusiasm and desire to wrath, worry, and depression (Carver *et al.*, 2010). Optimists maintain a positive outlook and anticipate favorable results, even in challenging situations, leading to a combination of relatively positive emotions, while pessimists anticipate unfavorable outcomes (Carver *et al.*, 2010). Carver *et al.* (2010) define optimism as an individual difference variable reflecting the degree to which people generally have positive expectations about the future. This research derives overoptimism from the definitions of optimism and optimists by Carver *et al.* (2010) and the concept of overoptimism by

Schade and Koellinger (2007). Accordingly, it is defined as the tendency to be very optimistic about the risky external environment, resulting in heightened confidence and perseverance when confronting numerous problems, especially in the face of delayed or arduous progress.

According to Shane and Venkataraman (2000), in many industries, most new companies fail, and few succeed in replacing incumbents, indicating that entrepreneurs who take advantage of these opportunities are very optimistic about the value that they discover. The authors suggest that overoptimism motivates opportunities by limiting information, stimulating excellent future forecasts, triggering a search for relatively small amounts of information, and causing people to act first and then analyze. Overoptimism causes entrepreneurs to be very optimistic about customer demand and the ability to control future matters and company performance (Verheul & Carree, 2007).

Lowe and Ziedonis (2006) show that founders continue technology development efforts for longer periods amidst market uncertainty. This consistency in product or technology development efforts over a long period shows the overoptimism of founders in developing new products (Lowe & Ziedonis, 2006), represented by NPDS. Research also shows that start-ups achieve economic returns (NVP) after being acquired by an established firm. This leads to the following two hypotheses:

H₃: Overoptimism positively influences NPDS.

H₄: Overoptimism positively influences NVP.

Research Methods

This study employed a quantitative methodology, utilizing a cross-sectional survey to achieve its research objectives. Quantitative research typically focuses on establishing cause-and-effect correlations and commences with the formulation of a hypothesis (Gunter, 2013). Surveys provide a primary method of quantitative research that does not entail any prior manipulation of participants or their conditions (Gunter, 2013). A cross-sectional survey was chosen as the research strategy as it is appropriate for investigating the EE domains and cognitive bias, particularly the overoptimism of founders of digital start-ups in Bogor and Depok, West Java, Indonesia. Online questionnaires were used for this cross-sectional survey.

The cross-sectional survey was followed by post-survey interviews with selected founders in Bogor to gain an understanding of founders' cognitive bias and external factors, such as the city's EE, as suggested by Kuter and Yilmaz (2001). Hence, the interviews should enable the authors to accurately interpret the statistical findings from the survey. Kuter and Yilmaz (2001) assert that interviews are flexible due to the interviewer's ability to adjust specific questions or their order based on the respondents' reactions, and they are participatory as they require the interviewer and participant to engage in an interactive dialogue. Face-to-face, structured interviews were chosen to guide and direct the interviews.

'Education and training' was assessed using eight indicators from De Winne and Sels (2010), Isenberg (2011), Nicotra *et al.* (2018), Tabares *et al.* (2015), and the World Economic Forum (2013). 'Workforce' was assessed using four indicators from Fish and Srinivasan (2012), Leendertse *et al.* (2022), Nicotra *et al.* (2018), and the World Economic Forum (2013). Together, these two components represent the human capital domain of the EE. 'Accessible markets' was assessed using four indicators from Blank (2018), Bosch *et al.* (2013), Haltiwanger and Jarmin (2000), Isenberg (2011), Kauffman and Walden (2001), Nicotra *et al.* (2018), and the World Economic Forum (2013). 'Formal networks' was assessed using four indicators from Aaboen and Aarikka-Stenroos (2017), Birley (1985), Colombo *et al.* (2010), and Neck *et al.* (2004), while 'informal networks' was assessed using four indicators from Birley (1985), Feld (2012), Neck *et al.* (2004), Norris (2002), and Spigel (2017). These three components represent the market domain of the EE. The cognitive bias of overoptimism was assessed using five indicators from Hmieleski and Baron (2009) and Scheier *et al.* (1994). All research variables were evaluated using a six-point Likert scale.

The snowball sampling approach—categorized as a non-probability sampling method—was chosen to identify, reach, and engage individuals from specific demographics when the researcher anticipates challenges in forming a representative sample of the study population (Cohen & Arieli, 2011). According to MIKTI (2021), the Jabodetabek agglomeration contributed 481 digital start-ups, accounting for 39.59% of the total digital start-ups in Indonesia in 2020. The city of Jakarta contributes 377 digital start-ups, or 78% of Jabodetabek's total (MIKTI, 2021). The authors sent surveys to

the available contacts in the MIKTI database via email. As there was no response from the contacts, the authors identified challenges and started the critical milestone with the MIKTI coordinated. The cities of Bogor and Depok were selected due to their proximity to Jakarta city, their presence of well-known universities, and the coordinator's social network. This study surveyed 51 founders in the cities of Bogor and Depok, which together had 43 digital start-ups in 2020 (MIKTI, 2021). Out of 51 respondents, 45 completed the questionnaire and belonged to the target demographic of founders. These founders are leading digital start-ups that have been operational for a minimum of three years and a maximum of eight years, thus qualifying as new ventures.

The collected data were examined using partial least squares structural equation modeling (PLS-SEM) with SmartPLS version 4.0.9.5 software. PLS-SEM is utilized to derive parameter estimates from the measurement model and analyze the hypothetical relationships between variables through the structural model. PLS-SEM is designed to address scenarios commonly seen in marketing research, namely the lack of symmetric distributions of variables assessed by a nascent or minimally consolidated theory, formative models, and/or a limited amount of data (Ringle *et al.*, 2015). PLS-SEM is selected due to the beginning phase of measured variables in the domains of EE and a limited amount of data to estimate a more complex model.

Results and Discussion

Respondent Demographic

In this study, 77.33% of the participants were male, 48.89% were in the age group from 20 to 29 years old, 55.56% had obtained a bachelor's degree, 64.45% were Javanese ethnics, 73.34% had previous work experience before building digital start-ups as founders, and 57.78% built their start-ups with their own funding (bootstrapping). Table 1 presents detailed demographic data concerning the respondents.

Reflective Measurement Model Assessment

This study employs a distinct two-step approach for higher-order constructs (HOCs), whereby the structural model assessment utilizes the outcomes from the second stage (Sarstedt *et al.*, 2019). Measurement begins with the acquisition of latent variable scores (LVSs), which are

Table 1
Demographic respondents

	Demographic	Frequency	%
Gender	Male	33	73.33
	Female	12	26.67
Age group	20-29	22	48.89
	30-39	18	40.00
	40-49	4	8.89
	50-59	1	2.22
Education	Up to high school	5	11.11
	Associate degree	10	22.22
	Bachelor's degree	25	55.56
	Postgraduate	5	11.11
Ethnics	Banjar	1	2.22
	Betawi	1	2.22
	Bugis	1	2.22
	Javanese	29	64.45
	Malay	1	2.22
	Minangkabau	1	2.22
Sundanese		11	24.45
Previous work experiences	No work experience	2	4.44
	Up to 5 years	33	73.34
	6 to 10 years	4	8.89
	11 to 15 years	1	2.22
	16 to 20 years	3	6.67
	More than 20 years	2	4.44
Funding	Bootstrapping	26	57.78
	Pre-seed funding	17	37.78
	Seed funding	2	4.44

Source: Own study

subsequently included in the dataset before being reintroduced into PLS-SEM. The HOC indicator represents the lower-order construct (LOC) variable. The assessment of the LOC variables in this study is based on the reflective measurement model test to determine their quality. The evaluation of construct quality adheres to the methodology proposed by Hair *et al.* (2019), which begins with a factor loading test and is followed by tests of reliability, convergent validity, and discriminant validity. Following Hair *et al.* (2019), the recommended value for factor loading is 0.708. However, six indicators with values above 0.638 are retained for further analysis due to their importance. A factor loading value exceeding 0.6 is preserved as it signifies the efficacy of items in assessing the latent variable (Hoque *et al.*, 2018). Cronbach's alpha and composite reliability are used for assessing reliability, whereby the composite reliability values have a minimum threshold of 0.70 (Hair *et al.*, 2011). Cronbach's alpha has a minimum threshold of 0.6, which provides a reliable measure of internal consistency (Hoque *et*

al., 2018). Therefore, the construct reliability is fulfilled. The results demonstrate that the average variance extracted (AVE) is above the minimum criterion of 0.5, as recommended by Hair *et al.* (2019), hence confirming that convergent validity is not an issue. Table 2 presents the factor loading, reliability (composite reliability and Cronbach's alpha), and convergent validity (AVE) values.

Table 2
Summary of measurement model

Latent variable	Indicator	Loading	AVE	Composite reliability	Cronbach's alpha
Workforce	MPSD2	0.688	0.589	0.810	0.654
	MPSD3	0.851			
	MPSD4	0.755			
	MPPD1	0.872			
Education & training	MPPD2	0.733	0.611	0.886	0.850
	MPPD5	0.815			
	MPPD6	0.829			
	MPPD7	0.638			
	MFMA1	0.747			
Accessible market	MFMA2	0.747	0.543	0.826	0.721
	MFMA3	0.752			
	MFMA4	0.701			
	MSJF1	0.861			
Formal network	MSJF2	0.798	0.720	0.885	0.809
	MSJF3	0.885			
	MSJI1	0.702			
Informal network	MSJI2	0.932	0.618	0.826	0.704
	MSJI3	0.701			
	NPDS	NPDS1			
NPDS2	0.868				
NPDS3	0.773				
NVP	NVP1	0.859	0.671	0.890	0.834
	NVP2	0.829			
	NVP3	0.893			
	NVP4	0.679			
Overoptimism	OVOP1	0.757	0.630	0.871	0.803
	OVOP3	0.802			
	OVOP4	0.877			
	OVOP5	0.731			

Source: Own study

Note: MPSD = workforce represented by MPSD1-MPSD4; MPPD = education & training represented by MPPD1-MPPD8; MFMA = accessible market represented by MFMA1-MFMA4; MSJF = formal network represented by MSJF1-MSJF4; MSJI = informal network represented by MSJI1-MSJI4; NPDS = new product development success represented by NPDS1-NPDS3; NVP = new venture performance represented by NVP1-NVP4; OVOP = overoptimism represented by OVOP1-OVOP5

This study employs the heterotrait-monotrait ratio (HTMT) to evaluate discriminant validity. Discriminant validity problems occur if the HTMT values exceed the threshold of 0.90 (Hair *et al.*, 2019). The HTMT value of the correlation between informal networks and formal networks is 0.905, although it remains within the threshold of 0.90 when rounded. Therefore, the test results support the establishment of discriminant validity

according to the HTMT. Table 3 shows the HTMT values between the variables.

Table 3
Heterotrait-Monotrait (HTMT)

	AM	ET	FN	IN	NPDS	NVP	Ovop
ET	0.315						
FN	0.695	0.342					
IN	0.497	0.279	0.905				
NPDS	0.459	0.193	0.426	0.364			
NVP	0.867	0.182	0.573	0.514	0.616		
Ovop	0.735	0.484	0.687	0.462	0.724	0.800	
Workforce	0.780	0.577	0.868	0.501	0.482	0.445	0.778

Source: Own study

Note: AM = accessible market; ET = education & training; FN = formal network; IN = informal network; NPDS = new product development success; NVP = new venture performance; Ovop = overoptimism

Reflective Measurement Model Higher Order Construct (HOC) Assessment

Table 4
Summary of HOC measurement model

Latent variable	Indicator	Loading	AVE	Composite reliability	Cronbach's alpha
Human capital domain	Education & training	0.789	0.707	0.828	0.593
		0.890			
		0.793			
Markets domain	Formal network	0.900	0.682	0.865	0.768
		0.779			
		Informal network			

Source: Own study

The HOC indicators for the market domain comprise the three LOC variables of 'accessible markets,' 'formal networks,' and 'informal networks,' while the HOC indicators for the human capital domain encompass 'education and training' and 'workforce.' The HOC measurement initiates with the evaluation of factor loading, collinearity, reliability, construct reliability, and construct validity, which includes convergent validity (AVE) and discriminant validity (HTMT; Sarstedt *et al.*, 2019). The factor loadings are above 0.708, while the VIF values for the indicators span from 1.216 to 2.535. A VIF value below a conservative value of 3 indicates the absence of collinearity issues (Hair *et al.*, 2019). The composite reliability values have a minimum threshold of 0.70, while the Cronbach's alpha has a minimum threshold of 0.6. The 'human capital domain' HOC variable has a value of 0.593, which falls within the threshold of 0.6 when rounded. Therefore, construct reliability is fulfilled. The AVE values are above the

minimum criterion of 0.5, hence confirming that convergent validity is not an issue. Table 4 presents the factor loading, reliability (composite reliability and Cronbach's alpha), and convergent validity (AVE) of the HOC measurement model.

The HTMT values of HOC do not exceed 0.90, and hence the test results support the establishment of discriminant validity according to the HTMT. Table 5 shows the HTMT values of HOC between the variables.

Table 5
Heterotrait-Monotrait (HTMT) of HOC

	HCD	MD	NPDS	NVP
MD	0.807			
NPDS	0.415	0.478		
NVP	0.366	0.741	0.616	
Overoptimism	0.872	0.784	0.724	0.800

Source: Own study

Note: HCD = human capital domain; MD = markets domain; NPDS = new product development success; NVP = new venture performance

Structural Model Assessment

The structural model is assessed utilizing the coefficient of determination (R^2), cross-validated redundancy (Q^2), and path significance (Hair *et al.*, 2019). The dependent variables in this study—NPDS, NVP, and overoptimism—have R^2 values greater than 0.1. Hence, predictive ability is formed. Next, Q^2 establishes the predictive significance of the endogenous construct (Hair *et al.*, 2019). The Q^2 value must exceed zero to establish the positive accuracy of the structural model for a construct (Hair *et al.*, 2019). The Q^2 values of the dependent variables are indeed greater than zero. The next test involves hypothesis testing to ascertain the significance of the established relationships. The findings of the direct relationship test are presented in Table 6, where the link is deemed statistically significant if the P-value is below 0.05 (Hair *et al.*, 2019).

Table 6
Testing results of the structural model

Hypothesis Testing	BC	SD	TS	PV	Decision
H1 HCD → Ovop	0.376*	0.185	2.035	0.042	Accepted
H2 MD → Ovop	0.422**	0.151	2.797	0.005	Accepted
H3 Ovop → NPDS	0.583***	0.116	5.026	0.000	Accepted
H4 Ovop → NVP	0.660***	0.125	5.265	0.000	Accepted
R^2					
NPDS	0.340	0.072			
NVP	0.435	0.222			
Ovop	0.505	0.382			

Source: Own study

Note: BC = beta coefficient; SD = standard deviation; TS = T Statistics; PV = P Values; HCD = human capital domain; MD = markets domain; Ovop = overoptimism; significant * $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$

The results of this study confirm that all hypotheses are validated. The findings confirm that the human capital domain has a positive influence on overoptimism, as articulated in H1. The accessibility of education and training among individuals with university or polytechnic backgrounds and professional certifications is crucial for founders to sustain their entrepreneurial endeavors and achieve scalability. The significance of the human capital domain is further affected by the educational qualifications of the founders in this sample. The sample shows that 22.22% of respondents possess an associate degree, 55.56% hold a bachelor's degree, and 11.11% have a post-graduate degree, thus elucidating why the human capital domain significantly and positively affects overoptimism. This finding supports previous studies by Sellar and Zipin (2019), which suggest that human capital cultivates positive traits such as overoptimism. Additionally, Verheul and Carree (2007) found that entrepreneurs possessing extensive general knowledge acquired through education also exhibit overoptimism. This finding aligns with a comment made by the study's post-survey interviewee in the city of Bogor, who stated that:

“A partnership was established with Institut Pertanian Bogor to develop a plant encyclopedia. Partnering with universities is advantageous for founders in acquiring talents that increase founder overoptimism”

The study demonstrates that the market domain positively affects overoptimism, as stated in H2. The market domain opens expansion opportunities that influence founders' overoptimism. The expansion is performed through accessible markets, formal networks, and informal networks. In both formal and informal networks, a higher degree of overoptimism is correlated with larger networks and stronger social ties. The finding underscores the significance of social resources, whereby individuals within larger social networks have access to more socially valued resources, hence increasing the likelihood of cultivating positive future expectations and a higher level of overoptimism (Nes & Segerstrom, 2006). Hence, this finding supports previous studies by Amănalăchioaie *et al.* (2025), Javalgi *et al.* (2012), and Brissette *et al.* (2002). In addition, this finding is strengthened with a comment made by the study's post-survey interviewee in the city of Bogor, who stated that:

“Accessible market expanded throughout the pandemic, with social media growth surging from 15,000 to 90,000 in less than a year, hence amplifying overoptimism”

This study indicates that overoptimism positively influences NPDS, corroborating hypothesis H3. The founder’s capacity to change by retracting established goals and reassessing prior events and efforts—whether successful or unsuccessful—is crucial for navigating dynamic market conditions and preventing failure as a start-up (Trevelyan, 2008). Founders exhibiting overoptimism persist in advancing their ideas or innovations despite new information or hurdles (Lowe & Ziedonis, 2006; Trevelyan, 2008). This knowledge is essential for adapting products or services to changeable market conditions. By remaining receptive to new information and consistently adapting products or services, these innovations can outperform competitors, capture new markets, and fulfill consumer requirements. This finding corroborates the study conducted by Lowe and Ziedonis (2006).

This study suggests that overoptimism has a positive influence on NVP, thereby validating hypothesis H4. The founders of the digital start-ups in this study experienced uncertainty due to their effective navigation of the Covid-19 epidemic. They adeptly adjusted to and maneuvered through fluctuating market conditions, as demonstrated by four indicators of overoptimism that align with their expectations. The founders persisted in their entrepreneurial endeavors, as the businesses had been operational for a minimum of three years during the sample collection period from July to December 2023, indicating that the companies effectively navigated the pandemic. The founders prolonged their technological development endeavors during a period of uncertainty, reflecting overoptimism. This finding supports the previous study by Lowe and Ziedonis (2006).

Conclusions and Implications

The introduction of innovative products and services by digital start-ups can significantly influence national growth and enhance a country’s competitiveness (Müller & Rammer, 2012). This study demonstrates that the two foremost EE domains as identified by the World Economic Forum’s EE heatmap—namely the market and human capital domains—are pivotal in facilitating digital start-ups through market dynamics. The

two domains empirically influence founders’ cognitive bias of overoptimism. This study empirically validates the previous study by Isenberg (2010), which observed the impact of the EE on cognitive bias. The significance of two EE domains on founders’ cognitive bias will extend their efforts in developing innovative products and services, or enhance the start-ups’ performance.

This study empirically demonstrates that overoptimism affects NPDS and NVP. The findings suggest that overoptimism enables founders to continuously develop new products during the uncertain period and for a longer time (three to eight years, as evidenced in this study’s sample). The resilience in pivoting new products and services that fit markets would open opportunities for untapped markets due to the dynamic and uncertain conditions. Overoptimism among founders is found to be critical when they face challenging conditions. Hence, the study suggests that founders must possess overoptimism to sustain resilience and prolong their entrepreneurial endeavors in a volatile and uncertain landscape.

This study has several limitations, notably the sample size, which might not be sufficiently representative of the overall founders of digital start-ups in Bogor and Depok (Indonesia); the main limitation of this study is the weak generalizability of the findings. However, we argue that the same EE domains that influence the overoptimism of the founders in Bogor and Depok may influence the overoptimism of other founders in the same digital start-up industry in any other cities in Indonesia. We, consequently, expect to see other studies in other cities of Indonesia or other emerging economies to enhance our comprehension on how EE domains influence the cognitive bias of the founders. As there are function differences between the two main cognitive biases of overoptimism and overconfidence (Bernoster *et al.*, 2018), future studies could examine the influence of the other main cognitive bias of overconfidence or other biases on NPDS and NVP. In addition, future research should seek to validate the other four EE domains identified by Isenberg (2011) in Bogor and Depok, as well as in other cities in Indonesia or other emerging economies.

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