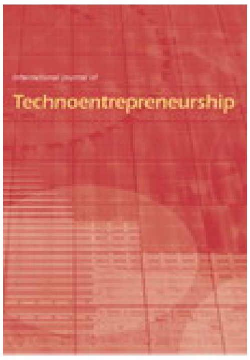

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Driving factors for the use of business intelligence and analytics among Indonesian startups

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Abstract: This study investigates the influence of market turbulence, technological turbulence, competitive intensity, data-driven culture, and resource accessibility on the use of business intelligence and analytics technology in startup companies in Indonesia. The study was conducted through a survey and received 44 responses from startup companies. The results show that technological turbulence and a data-driven culture are driving factors in the use of business intelligence and analytics technology as a strategic tool for startup companies. These empirical findings enrich the study of the driving factors for business intelligence and analytics technology usage in addition to the TOE framework, i.e., based on the strategic management framework, which takes perspective from the external and internal environment. This study concludes two managerial implications, emphasising the importance of a data-driven culture and the need to carefully monitor technological turbulence in an effort to encourage business intelligence and analytics technology usage as a strategic tool for startups.

Keywords: business intelligence and analytics; driving factor; data-driven culture; technological turbulence; startups.

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1 Introduction

In today's digital era, people generate a lot of data all the time from various sources, through various digital media platforms and digital services which then lead to a big data ecosystem and business analytics (Pappas et al., 2017). Startups and entrepreneurs use data to increase value, gain competitive advantage, and improve various aspects of society (Berg et al., 2018; Otero and Peter, 2014). Startup is a new venture that produces cutting-edge technology and has a huge impact on the global economy (Giardino et al., 2016). In the context of extreme uncertainty and limited economic, human and physical resources, startups have unique challenges related to product development and their innovation methods (Giardino et al., 2015). Startups operate in high-risk, fast-changing and competitive environments, which is why continuous experimentation is essential to quickly learn about and bring products to market (Berg et al., 2018). There is an increasing literature on how big data analytics can generate business or social value (Mikalef et al., 2017). Digitisation and big data analytics can be strategic tools to reduce enterprise failure rates (Weiß et al., 2018). The role and breadth of data analysis in startups remains to be explored because its use can be a major success factor in an increasingly competitive business landscape (Mikalef et al., 2017).

The evolution of the digital economy and its combination with data analytics has allowed many startup companies to create business models that challenge the business models of established companies (Chen et al., 2012). The main goal of startups is to accelerate product development in the early stages and streamline the learning process (Nguyen-Duc et al., 2017). Startups must respond to rapidly changing customer needs and demands (Bosch, 2015) both by speeding up the decision-making process and the design process (Pantiuchina et al., 2017). The design process acceleration is carried out using a prototype iteration approach to validate product-market fit quickly (Berg et al., 2018).

Startups are also data-driven innovation engines. The use of business analysis for organisational value creation depends on its role in the organisation's decision-making process (Helfat and Peteraf, 2009; Teece et al., 1997). Some literature shows examples of big data initiatives and constructs them as dynamic capabilities that help create business knowledge with the aim of increasing value, performance, and competitive advantage, in the midst of dynamic market conditions, however, many top managers are still hesitant and reluctant to allocate their resources on a regular basis to facilitate that initiative (El-Kassar and Singh, 2019). Startups face various challenges, especially related to the limited availability of resources and dependence on external technology factors (Ronkainen and Abrahamsson, 2003), and those challenges impact their ability to use big data and analytics to generate value (Berg et al., 2018). On the other hand, many startups point out that generating knowledge from data analytics is not their main goal, so it is not included in their overall business strategy (Berg et al., 2018).

The use of Business Intelligence & Analytics (BI&A) varies from the public sector, real estate evaluation, valuation (Sun et al., 2020), to healthcare management (Chinnaswamy et al., 2019). Data analytics as a capability will affect the company's performance by process orientation (Fosso Wamba et al., 2017) and through value (Fosso Wamba et al., 2019). Data utilisation has high operational and strategic potential for business value creation (Gobble, 2013), because it helps generate actionable ideas for company performance and competitive advantage (Fosso Wamba et al., 2017). Data utilisation is a potential thing for improving company business performance, especially for startups as digital native business entities. However, data utilisation even for startups is not optimal. BI&A is a tool used in terms of utilising data, obtaining data and generating useful information for startups. Llave (2019) conducted a review and found that BI&A research is needed in developing countries, across industries, how it generates value and the factors that influence the process.

2 Literature review and hypotheses development

Business Intelligence is primarily used by decision makers to improve the quality of the decision-making process (Negash and Gray, 2008). Previous research has shown that investment in BI&A is a necessary but not sufficient condition for value creation and benefit realisation (Hannula and Pirttimaki, 2003; Ransbotham et al., 2016; Yeoh and Popovič, 2016). Using the dynamic capabilities point of view Božič and Dimovski (2019) defines the use of BI&A in organisations as low-level dynamic capabilities that organisations can leverage to create cutting edge knowledge in dynamic environmental settings. BI&A enables organisations to define knowledge creation routines as an important dynamic capability and to process large amounts of information through information processing capabilities, thereby facilitating knowledge creation (Chen et al., 2015; Olszak, 2014; Shollo and Galliers, 2016). Furthermore, several studies have proven that BI&A has an influence on startup performance, both through the ability to balance innovation (Božič and Dimovski, 2019) as well as through strategic activities such as network learning (Caseiro and Coelho, 2019) and entrepreneurial orientation (Caseiro and Coelho, 2018).

BI&A is basically a tool used in terms of utilising data, obtaining data and generating information that has a strategic role for startups. Llave (2019) conducted a review and found that BI&A research is needed in developing countries, across industries, how it generates value and the factors that influence the process. Previous research related to the factors that influence the use of BI&A generally uses technological-environmental-organisational (TOE) framework (Aldossari and Mukhtar, 2019; Lautenbach et al., 2017; Malladi and Krishnan, 2013; Nam et al., 2019), and using an environmental approach (Moreno et al., 2020). From a strategic management point of view, which is, the first step is environmental scanning (David and David, 2017; Wheelen et al., 2017), then the use of BI&A as a strategic tool is also influenced by the external and internal environment. So this study focuses on analysing the factors that influence the use of BI&A in startups from its internal and external environment.

2.1 Market turbulence

Companies often experience market and technology turbulence. According to Calantone et al. (2003), a volatile environment is defined as a market with a high rate of change, leading to uncertainty and predictability, dynamic and unstable conditions with sharp discontinuities in demand and growth rates, temporary competitive advantages and low barriers to entry and exit, which constantly change the competitive structure of an industry. In other words, market turbulence is related to the degree of instability and uncertainty in the firm's market (Jaworski and Kohli, 1993), and is more prevalent in developing country (Halme et al., 2012). Market turbulence is also characterised by continuous changes in customer preferences and demands (Jaworski and Kohli, 1993), in the price and cost structure and in the composition of competitors (Kawai et al., 2020). Thus, in a volatile environment, managers must face the uncertainty associated with customer needs, as well as the best long-term technology and market paths to follow and what resources to invest in various efforts (Calantone et al., 2003; Mullins and Sutherland, 1998). Market turbulence also affects startup performance through bricolage as strategic activities (Dos Santos et al., 2020). Furthermore, Lautenbach et al. (2017) proves that market turbulence has an influence on the use of BI&A.

H1: Market turbulence has a positive effect on BI&A in startups

2.2 Technological turbulence

Technological innovations can also trigger environmental turbulence by accelerating the pace of change both in the scientific community and in the marketplace. This causes the product to obsolete faster, so the company may be able to enjoy a competitive advantage in a shorter time (Calantone et al., 2003). Lichtenthaler (2009) argues that depending on the level of environmental turbulence, companies learn to do business through the integration of technology and market knowledge. According to Lichtenthaler (2009), technological turbulence is one factor in a company's external environment, besides market turbulence and competitor competition. Technological turbulence defined as "the rate of technological change in an industry" (Jaworski and Kohli, 1993). On the other hand, technological turbulence creates entrepreneurial opportunities and presents challenges for established companies and so is the market (Hall and Rosson, 2006). Technological turbulence has also been shown to affect startup performance through bricolage behaviour as a strategic activity (Dos Santos et al., 2020).

Moreno et al. (2020) found that the use of BI&A has an effect on marketing operational capabilities through dynamic capabilities, but market turbulence and technological turbulence are not proven to moderate this effect. This means that the relationship between the use of BI&A with market turbulence and technological turbulence is not a moderation. Pressure from environmental turbulence requires a fast and targeted response from startup so that they can survive by utilising their information and information technology capabilities (Ravichandran, 2000). However, Malladi and Krishnan (2013) proves that environmental dynamism has no effect on the use of BI&A technology, however they suggest this needs to be investigated further in a value-oriented BI&A context. Thus, this study seeks to confirm whether technological turbulence has an influence on the use of BI&A technology.

H2: Technological turbulence has a positive influence on BI&A in startups

2.3 Competitive intensity

The environment in which new businesses establish their activities influences most of the effort required to develop legitimacy and the expected results (Kawai et al., 2020). Tornikoski and Newbert (2007) suggest that understanding industry dynamics is very important because the use of resources and subsequent strategies that entrepreneurs choose are also influenced by the intensity of competition. Competitive Intensity can be defined as "a situation where competition is fierce due to the number of competitors in the market and the lack of potential opportunities for further growth" (Auh and Menguc, 2005). In a highly hostile and competitive market, competitors are constantly putting pressure on each other and it is not easy to predict competitors' strategies and capabilities as competition changes irregularly (Martin and Javalgi, 2016; Slater and Narver, 1994).

Startups that operate in industries with a high level of competitive intensity but have sufficient resources will utilise their resources more effectively and flexibly in identifying and overcoming increasingly intensive competitive pressures (Levinthal, 1997; Sirmon et al., 2007). On the other hand, startups facing critical resource constraints may be hesitant to invest further in new market opportunities (Sirmon et al., 2007) and to take risks (Cui et al., 2005) in facing an increasingly competitive market environment. In addition, in competitive market conditions, startups can see resources as something more valuable, utilise them efficiently and make competitive moves, thereby influencing strategic changes (Kraatz and Zajac, 2001; Sapienza et al., 2006). Pressure from high competition encourages startups to be able to maintain their competitive advantage through the use of data and information by using BI&A technology (Malladi and Krishnan, 2013). Nam et al. (2019) found that competitive pressures drive BI&A adoption at the initiation stage. Thus, the higher the competitive pressure faced will increase the use of BI&A technology in startups.

H3: Competitive intensity has a positive influence on BI&A in startups

2.4 Data driven culture

Several previous studies have emphasised that to take advantage of BI&A in order to gain competitive advantage, companies need to develop a data-driven culture where managerial decisions rely more on data-driven insights (Davenport et al., 2001; Kiron et al., 2012; Kiron and Shockley, 2011; LaValle et al., 2011). According to Kiron et al. (2012) data-driven culture refers to "patterns of behaviour and practices by a group of people who have a belief that owning, understanding, and using certain types of data and information plays an important role in the success of their organisation". This basically requires good coordination of BI&A activities so that it requires strategic guidance, organisational policies and rules, and their business processes (Kiron et al., 2012; Kiron and Shockley, 2011; LaValle et al., 2011). Duan and Cao (2015) found that data-driven culture has an influence on startup performance through its strategic activities. Nam et al. (2019) found that data-related factors have a significant influence in each stage of BI&A adoption and they also give a notion of the importance of data-driven culture in BI&A adoption.

H4: Data-driven culture has a positive influence on BI&A in startups

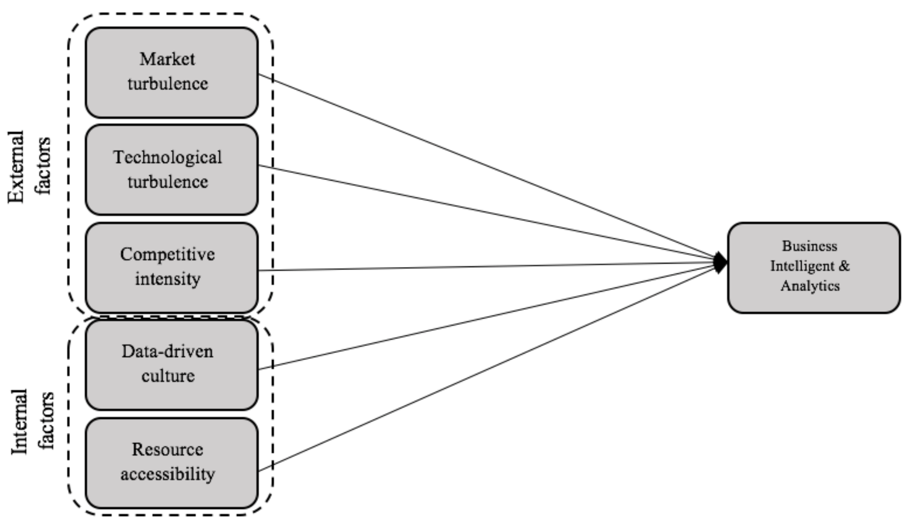
2.5 Resource accessibility

Kawai et al. (2020) defines resource accessibility for startups as the ability to acquire and utilise resources that entrepreneurs can leverage to outperform their peers. Compared to large companies, startups have a greater chance of experiencing resource scarcity which often leads to a higher risk of failure (Stinchcombe, 1965). Having special access to valuable resources enables startups to develop the strategic capabilities needed to recognise and exploit new business opportunities even in a volatile market environment (Chen et al., 2015; Edelman and Yli–Renko, 2010). On the other hand, startups with a shortage of critical resources will have difficulty finding and exploiting business opportunities in new markets because the lack of accessibility of resources tends to reduce their ambition and confidence in achieving their business goals (Krueger, 2000). Startup as a new venture has limited resources, so in order to be able to face the competition, it is necessary to utilise its resources efficiently. Therefore, strategic capabilities are needed for startups to survive. BI&A is a strategic tool that can improve startup performance (Kasemsap, 2016; Kawai et al., 2020). Therefore, it is reasonable to suspect that access to resources plays an important role in encouraging startups to use BI&A.

H5: Resource accessibility has a positive influence on BI&A on startups

The formulation of the conceptual framework based on the development of the hypothesis is depicted in Figure 1.

Figure 1 Conceptual framework



3 Methodology

3.1 Measurement

This study uses quantitative analysis and involves multiple variables. Measurement of BI&A usage using ten items adopted from Božič and Dimovski (2019). The purpose of the measurement is to determine whether BI&A supports startups in monitoring consumers, markets, and competition; track internal and external knowledge flows; pursuing, generating and storing knowledge; and in retrieving and using the knowledge that has been gathered. All items were measured using seven Likert scales, ranging from 1 ("strongly disagree") to 7 ("strongly agree").

Market turbulence is measured using three indicators adopted from Dos Santos et al. (2020). All indicator items use seven interval scales using a semantic differential ranging from 7 ("very high/very large") to 1 ("very low/very few"). Technological turbulence is measured using five indicators adopted from Yang and Tu (2020). All indicator items use seven interval scales using a semantic differential ranging from 7 ("very high/very difficult") to 1 ("very low/very easy"). Competitive intensity is measured using three indicators adopted from Kawai et al. (2020). All indicator items use seven interval scales using a semantic differential ranging from 7 ("very large/very high") to 1 ("very little/very low"). Data-driven culture is measured using five indicators adopted from Duan and Cao (2015). The data-driven culture variable is formative so one global item is added for the purpose of measuring convergent validity. This global item covers all dimensions, namely confidence, openness, dependence, use, and need for data in decision making. All indicator items use seven interval scales using a semantic differential ranging from 7 ("strongly agree") to 1 ("strongly disagree"). All indicators for each variable are presented in Table 1. Resource accessibility is measured using three indicators adopted from Kawai et al. (2020). All indicator items use seven interval scales using a semantic differential ranging from 7 ("strongly agree") to 1 ("strongly disagree").

3.2 Sample and data collection

The population in this study is a member of one of the startup communities in Indonesia, totalling 4285 members with 187 startups. The selected respondents are those who understand data or the use of BI&A technology such as managers or executives above them, business analysts, insights, R&D, product development, and so on. The survey was conducted online by sending an electronic questionnaire to 187 startup contacts who are members of the community. Several items such as the name of the startup company, line of business, position in the startup company are also included to obtain the demographic profile of the respondents. One of the purposes of this is to determine the eligibility of respondents with the criteria set out in the study.

Of the 187 startup companies, 50 respondents filled out the questionnaire and 44 of them filled it completely and met the respondent's criteria. The majority of respondents are engaged in the e-commerce business (36%), followed by SaaS (16%), education technology (14%), IoT (7%), IT solutions (5%), software house (5%), messaging (5%), robotics (4%), big data (4%), financial technology (2%), and community builders (2%). Meanwhile, based on the year of establishment, the most established in 2020 (27%), followed by 2021 (20%), 2017 (16%), 2019 (14%), 2016 (14%), 2018 (5%), and 2015 (5%). Based on position, the majority of respondents are executives (77%), managers (20%), and staff (2%). Based on their experience, only 36% have ever joined a business incubator and/or accelerator, while the rest (64%) have never joined business incubator and/or accelerator.

Table 1 Variable operationalisation

Variable	*Code*	*Indicator*
BI&A	BIA1	System for formatting or categorising knowledge processes
	BIA2	Business intelligence and analytics technology to monitor competition and business partners
	BIA3	Business intelligence and analytics technology to enables collaboration among employees of different division in the organisation
	BIA4	Business intelligence and analytics technology to enables people in multiple locations can learn as one group
	BIA5	Technology intelligence and business analytics to look for new knowledge
	BIA6	Technology intelligence and business analytics to map specific knowledge sources
	BIA7	Intelligence technology and business analytics to gain product and process insights
	BIA8	Technology intelligence and business analytics to capture market and competition insights
	BIA9	Business intelligence and analytics technologies to generate and store insights about customers, partners, employees or suppliers
Data-driven culture	DDC1	The belief that owning, understanding and using data plays a critical role
	DDC2	Openness to new ideas and approaches as long as they are based on information/data
	DDC3	Decision making relies on data-driven insights
	DDC4	Data-driven insights in creating new products/services
	DDC5	Having sufficient data necessary to make a decision
Market turbulence	MT1	Number of similar subscriber or customer as before
	MT2	Market share stability among competitors
	MT3	Easiness to predicts customer demand
Technological turbulence	TT1	The rate of technological change
	TT2	The degree of opportunity created by technological change
	TT3	The number of new concepts/products due to technological breakthroughs
	TT4	The nature of technological development
	TT5	Difficulty to predicts the trend of technology in the next 2–3 years
Competitive intensity	CI1	Number of competitors
	CI2	Possible emergence of new competitors
	CI3	Number of substitute products
Resource access	RA1	The ability to acquire the necessary resources to support a new idea
	RA2	The ability to obtain additional resources to run the business/company
	RA3	Having access to resources

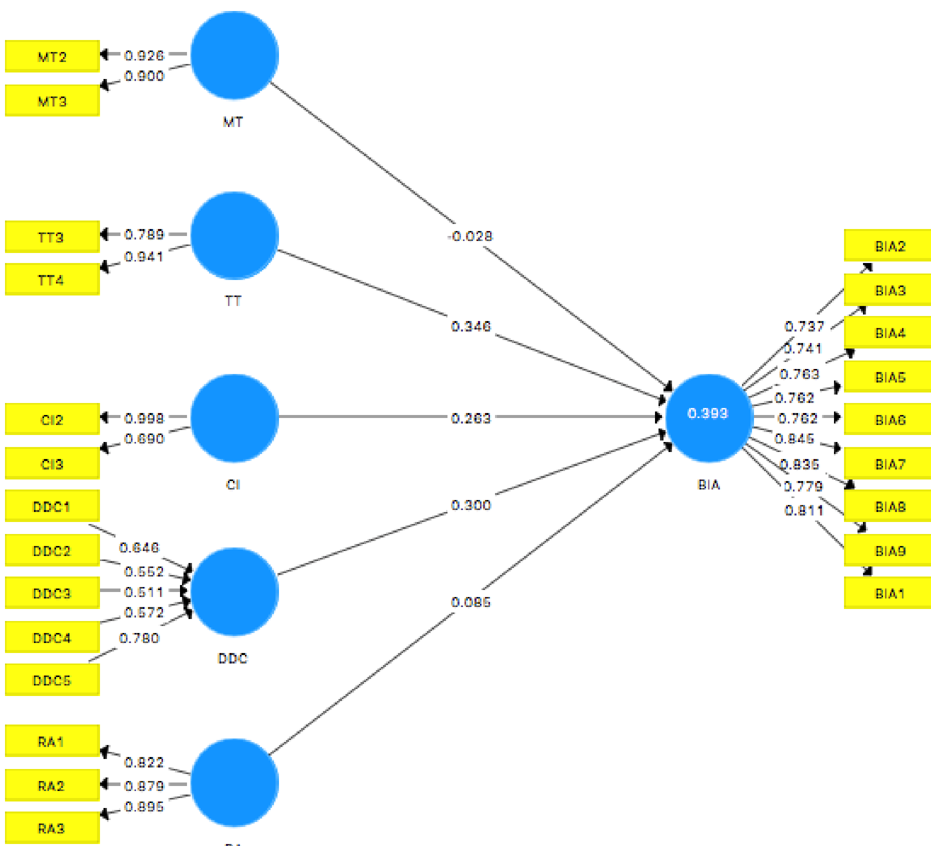
Hypothesis testing is done by modelling partial least squares (PLS) structural equations, using SmartPLS 3.3 software. PLS is proven to be reliable for adequately modelling reflective and formative constructs and requires a smaller sample than covariance-based SEM (Hair et al., 2017).

4 Results

4.1 Measurement model assessment

After calculating using the PLS algorithm, it was found that several indicators had a loading factor value of less than 0.7. Some items that have a loading factor of less than 0.7 are removed to increase reliability, but for formative variables, the loading factor criterion of 0.5 is used (Henseler et al., 2015). The items that been removed are presented in Table 2. After several items were deleted, the measurement model results were obtained as shown in Figure 2.

Figure 2 Measurement model (see online version for colours)



After obtaining the loading factor for all items having a value of more than 0.7 (except CI3 slightly below 0.7 so that it can still be included), then the model reliability calculation is carried out. The findings from Table 3 indicate that the composite reliability results for all reflective variables surpass the threshold of 0.7. Similarly, Table 4 reveals that the average variance extracted (AVE) values for all reflective variables exceed the threshold of 0.5. Thus, both the composite reliability and AVE values satisfy the established criteria for ensuring model reliability, as proposed by Chin (1998) and Ringle et al. (2012).

Table 2 Removed items due to unsatisfying loading factors

Item	*Loading factor*
MT1	0.581
TT1	0.651
TT2	0.569
TT5	0.677
CI1	0.537

Table 3 Composite reliability

	Composite reliability
BIA	0.934
CI	0.844
DDC	–
MT	0.909
RA	0.900
TT	0.859

Table 4 Average variance extracted (AVE)

	AVE
BIA	0.612
CI	0.736
DDC	–
MT	0.834
RA	0.750
TT	0.754

To determine discriminant validity, the Fornell-Larcker criterion was used. From the result of Fornell-Larcker criterion as presented in Table 5, the model can be concluded as eligible because all AVE root values are greater than their correlation with the other variables. Based on the correlation between indicators and the corresponding latent variables as presented in Table 6, it can be concluded that the model meets the criteria. Likewise, the result of HTMT ratio as presented in Table 7 has value less than 1.

For formative variables, data-driven culture, it is found that the loading factor value of all indicators is above 0.5 so that it can be concluded satisfactory (Henseler et al., 2015). From the cross-loading criteria, it is found that all indicators have the greatest correlation with the latent variable. Meanwhile, to determine convergent validity using redundancy analysis, it was found that the R value of the reflective variable was 0.844 (See Figure 3) so that it can be concluded to meet convergent validity (Chin, 1998). In order to investigate the presence of multicollinearity, an analysis was performed on the outer VIF values. The findings presented in Table 8 indicate that all DDC indicators have outer VIF values below the threshold of 4, suggesting that there are no multicollinearity concerns within the formative DDC variables.

Table 5 Fornell-Larcker criterion

	BIA	*CI*	*DDC*	*MT*	*RA*	*TT*
BIA	0.782					
CI	0.376	0.858				
DDC	0.395	0.098				
MT	0.426	0.381	0.545	0.913		
RA	0.371	0.509	0.236	0.431	0.866	
TT	0.451	0.145	0.188	0.443	0.270	0.869

Table 6 Cross-loadings

	BIA	*CI*	*DDC*	*MT*	*RA*	*TT*
BIA1	0.811	0.244	0.293	0.186	0.333	0.302
BIA2	0.737	0.120	0.152	0.063	0.034	0.214
BIA3	0.741	0.179	0.341	0.552	0.352	0.352
BIA4	0.763	0.571	0.227	0.416	0.464	0.601
BIA5	0.762	0.371	0.234	0.323	0.286	0.208
BIA6	0.762	0.144	0.406	0.451	0.289	0.544
BIA7	0.845	0.430	0.328	0.289	0.347	0.283
BIA8	0.835	0.164	0.415	0.273	0.064	0.160
BIA9	0.779	0.099	0.373	0.167	0.084	0.107
CI2	0.396	0.998	0.117	0.383	0.519	0.155
CI3	0.037	0.690	–0.136	0.235	0.230	–0.007
DDC1	0.255	–0.194	0.646	0.076	0.231	0.070
DDC2	0.218	0.204	0.552	0.334	0.262	0.324
DDC3	0.202	0.083	0.511	0.504	0.225	0.064
DDC4	0.226	–0.040	0.572	0.243	0.287	0.245
DDC5	0.308	0.211	0.780	0.546	0.007	0.114
MT2	0.415	0.346	0.491	0.926	0.366	0.300
MT3	0.359	0.351	0.507	0.900	0.425	0.527
RA1	0.128	0.487	0.198	0.411	0.822	0.359
RA2	0.309	0.490	0.002	0.364	0.879	0.262
RA3	0.402	0.400	0.367	0.379	0.895	0.179
TT3	0.262	–0.080	0.159	0.086	0.158	0.789
TT4	0.476	0.244	0.171	0.563	0.285	0.941

Table 7 HTMT ratio

	BIA	*CI*	*MT*	*RA*	*TT*
BIA					
CI	0.321				
MT	0.443	0.427			
RA	0.384	0.526	0.536		
TT	0.462	0.253	0.541	0.385	

Figure 3 Redundancy analysis (see online version for colours)

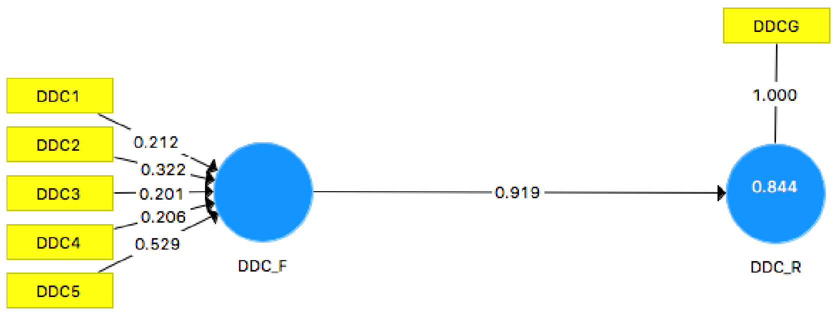


Table 8 Outer VIF DDC

	VIF
DDC1	1.142
DDC2	1.217
DDC3	1.377
DDC4	1.701
DDC5	1.416

4.2 Structural model assessment

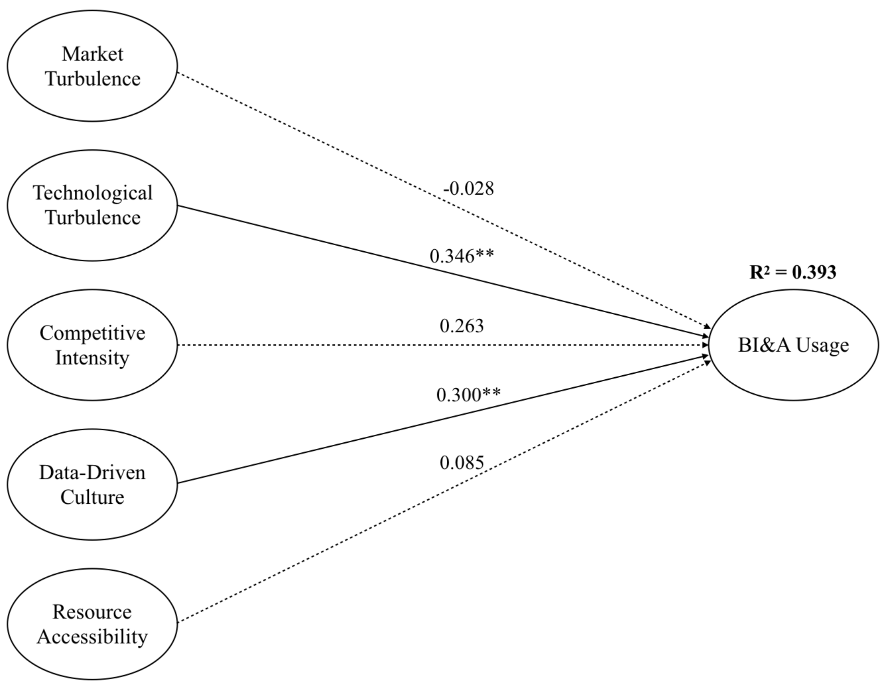
After testing the measurement model and the reliability and validity requirements are met, then the structural model is tested by using the one-tailed bootstrap method because the hypothesis is one-way. Hypothesis 1 which states that there is a positive effect of market turbulence on the use of BI&A is not supported based on the coefficient of influence and statistical significance ($\beta = -0.028$; $p = 0.435$). Hypothesis 2 which states that there is a positive effect of technological turbulence on the use of BI&A is supported by both the direction of the effect coefficient and its significance ($\beta = 0.346$; $p = 0.005$). Hypothesis 3 which states that there is a positive effect of competitive intensity on the use of BI&A is not supported even though it is slightly above the 0.1 ($\beta = 0.263$; $p = 0.106$) significance limit. Hypothesis 4 which states that there is an effect of data-driven culture is supported based on the coefficient of influence and significance

($\beta = 0.300$; $p = 0.043$). Hypothesis 5 which states that there is an influence of resource accessibility on the use of BI&A is not supported based on its significance ($\beta = 0.085$; $p = 0.339$). The complete hypothesis testing results can be seen in Table 9 and Figure 4.

Table 9 Hypotheses testing result

Hypothesis	*Path coefficient*	*Significance*	*Result*
Market Turbulence → BI&A	−0.028	0.435	Not supported
Technological Turbulence → BI&A	0.346	0.005	Supported
Competitive Intensity → BI&A	0.263	0.106	Not supported
Data-Driven Culture → BI&A	0.300	0.043	Supported
Resource Accessibility → BI&A	0.085	0.339	Not supported

Figure 4 Structural model result



*$p < 0.01$; **$p < 0.05$; ***$p < 0.001$.

Furthermore, by examining the f^2 values (refer to Table 10), it is possible to ascertain the effect size of each exogenous variable on BI&A, in addition to testing the hypothesis. Following the criteria from Cohen (2013) for the influence size of f^2 below 0.02 is small, 0.15 is medium, and 0.35 is high, then the size of the influence on BI&A from technological turbulence is high, and from data-driven culture and competitive intensity are medium. While the other two factors can be ignored since it has non-significant effect on BI&A and it is supported by the small f^2 value. Overall, the tested model is quite satisfactory that they are able to explain the BI&A by 39.3% (R2 = 0.393; Adjusted R2 = 0.313).

Table 10 Size effect f^2

	BIA
BIA	
CI	0.078
DDC	0.101
MT	0.001
RA	0.008
TT	0.154

5 Discussion and findings

The increasing role of data and information for business is common so that new forms of business today, namely startups, are the embodiment of strategic entrepreneurship, are required to be able to act strategically even since their establishment. One of the tools for making strategic decisions based on data and information is BI&A technology. Based on the strategic management framework, the first step taken before formulating a strategy is to carry out environmental scanning (Wheelen et al., 2017) or internal-external audit (David and David, 2017). Facing this turbulent or dynamic environment, BI&A's role is increasingly important. This study seeks to further uncover what factors drive the use of BI&A technology for startups. Several previous studies used the TOE framework to reveal some factors that drive the use of BI&A (Lautenbach et al., 2017; Malladi and Krishnan, 2013; Nam et al., 2019). Llave (2019) find a lack of research on BI&A in developing countries, across industries, how it generates value, and the factors that involved in the process. Several studies have found that BI&A affects startup performance through dynamic capabilities (Božič and Dimovski, 2019; Caseiro and Coelho, 2019) and entrepreneurial orientation (Caseiro and Coelho, 2018). In the context of Indonesia, a study by Triono and Rachman (2020) reveals the relationship of BI&A and startup performance. However, there is no research found on the factors that drives the use of BI&A in Indonesian startup. Thus, in the context of strategic entrepreneurship, this research contributes to identifying the factors that drive the use of BI&A in Indonesia.

The results of the model test find that the factor that has the biggest influence on the use of BI&A in startups in Indonesia is technological turbulence. This result supports the findings of Lautenbach et al. (2017), Malladi and Krishnan (2013), Nam et al. (2019) and Torres et al. (2018) that technological factors drive the use of BI&A.

Another factor that drives the use of BI&A at startups in Indonesia is the data-driven culture. From an organisational point of view, this finding also supports what was found by Malladi and Krishnan (2013) although it is not specific on cultural and is more of a managerial challenge. On the other hand, Nam et al. (2019) emphasises that organisationally, talent availability and culture are important in the BI&A assimilation stage.

The competitive intensity in this study is slightly above the 0.1 significance threshold and needs further investigation because it can almost be said to be significant in encouraging the use of BI&A. In addition, from the study of Malladi and Krishnan (2013 and Nam et al. (2019) that competitive intensity has a significant influence in encouraging the use of BI&A, and considering the conditions in Indonesia where the startup industry is growing rapidly, further research on this matter will be interesting to do.

The market turbulence factor has proven to have no significant influence in encouraging the use of BI&A at startups in Indonesia. This finding supports the study of Malladi and Krishnan (2013) even though this study uses a different construct as suggested, which is oriented to value creation. Findings from the study of Lautenbach et al. (2017) shows that external market factors encourage the use of BI&A by increasing competitive pressure, so that further study that is to examine the moderation or mediation effect of market factors on the use of BI&A.

Resource accessibility in this study proved not to have a significant effect on the use of BI&A on startups in Indonesia. A possible explanation for this finding is that startups are less focused on resource availability, they are more collaboratively oriented through the startup industry ecosystem, business incubators and accelerators, venture capital and other technology hubs. The main focus of startups is to meet market needs and build a prototype or MVP (Minimum Viable Product) (Bosch, 2015; Nguyen-Duc et al., 2017; Pantiuchina et al., 2017).

From a managerial point of view, this research provides an overview of the factors that drive the use of BI&A in startups. This is important for startups because the use of BI&A can increase value (Trieu, 2017), operational capability (Moreno et al., 2020; Yiu et al., 2020), strategic capability (Božič and Dimovski, 2019) even business performance (Caseiro and Coelho, 2018, 2019; Triono and Rachman, 2020). One factor that needs to be emphasised from this research is the data-driven culture. Having a culture that is aware of the importance of data at various levels of management will encourage and even increase the use of BI&A. At the top management level, the existence of a data-driven culture will help in creates commitment and support for the use of BI&A so that managerial challenges that mentioned by Malladi and Krishnan (2013) and Nam et al. (2019) can be resolved. As well as providing other benefits such as resource support and lowering organisational barriers (Lautenbach et al., 2017). Factors related to technology, in this study is technological turbulence, have also been proven to play a role in encouraging the use of BI&A so that startup managers need to pay attention, especially in implementing and fostering BI&A in their companies.

6 Conclusion

In the context of a complex and dynamic environment, as well as the availability of technology, BI&A is needed to improve the quality of organisational decision making which can result in better performance. The use of BI&A can also reveal conditions that are free from bias and offer knowledge that can be leveraged as a competitive advantage. Moreover, the use of BI&A has a strategic meaning in the context of the current digital economy, especially for startups as a manifestation of strategic entrepreneurship. In an effort to understand the driving factors for the use of BI&A in startups, this research departs from the strategic management framework, namely environmental scanning, external and internal environmental factors. An analysis of 44 technology startups in Indonesia found that the external factor that influences the use of BI&A is technological turbulence. Meanwhile, the internal factor that influences the use of BI&A is the data-driven culture. This study provides a different perspective on BI&A adoption, namely trying to use an internal-external environment approach, where other studies mostly use the TOE framework. The managerial implications of this research produce findings that can be followed up, especially regarding the role of data-driven culture.

7 Limitation and future research opportunities

This study has several limitations. The first is the small number of samples even though it has obtained multi-sector startup respondents. Further research needs to involve more respondents in order to be able to obtain more complete findings or wider generalisations. The second limitation is that this research does not identify the stages of the startup cycle, starting from the seed stage to exit. It would be more valuable if further research is able to identify this so that it can examine the relationship between BI&A use and the stage of the startup cycle. Some questions such as whether the use of BI&A is native at startup or occurs at an advanced level. Whether the use of BI&A has anything to do with the funding they get. How is BI&A oriented at each stage of the startup cycle, and several other questions that might be answered by identifying these stages. The next limitation is related to the variables involved as predictors of the use of BI&A in startups. Variables such as government support, technology industry climate, talent access or challenge, and several other variables outside this research need to be investigated further whether they have an impact on the use of BI&A. In addition, integration with the TOE framework can also be considered to get a more complete picture so as to be able to produce an integrative model of the driving factors for the use of BI&A in startups. Furthermore, the perceived usefulness of BI&A could be included in the model considering that the adoption of a technology also involves a tradeoff between risks and potential benefits.

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