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The Role of Business Capabilities in Supporting Organization Agility and Performance During the COVID-19 Pandemic: An Empirical Study in Indonesia

Albert Surya WANASIDA[1], Innocentius BERNARTO[2], Niko SUDIBJO[3], Agus PURWANTO[4]

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Abstract

This study aims to analyze the important role of business analytics capability, information quality, and innovation capability in influencing organization agility and organization performance during the Covid-19 pandemic. Data was collected from 76 companies from various sectors in Indonesia. Structural Equation Model-Partial Least Square (SEM-PLS) analysis was conducted to analyze the relationship between variables and test a series of hypotheses. Importance-Performance Matrix Analysis (IPMA), a useful analysis approach in PLS-SEM, is used, which extends the results of the estimated path coefficient (importance) by adding a dimension that considers the average values of the latent variable scores (performance). The IPMA approach examines not only the performance of an item but also the importance of that item. The results show that business analytics capability has a significant effect on information quality and innovation capability which then affects organization agility. Organizational performance is influenced by organizational agility. IPMA results show that organizational agility has the highest level of impact on organizational performance. This study will assist companies in planning business analytics, improving information quality, increasing innovation capability, and ultimately increasing agility and performance during the Covid-19 pandemic. This study will add to existing knowledge about previous literature, especially in the Covid-19 pandemic situation.

Keywords: Business Analytics Capability, Information Quality, Innovation Capability, Organization Agility, Organization Performance

JEL Classification Code: M31, L22, L25, O16

1. Introduction

Companies have widely embraced the use of analytics to streamline operations and improve processes. Business analytics gives an organization an excellent overview and insight on how companies can become more efficient, and these insights will enable such organizations to optimize and automate their processes. (Ashrafi et al., 2019). Business analytics can affect information quality and innovation capability (the organization's ability to carry out innovative practices) in organizations (Wang et al., 2015). Both then increase the company's agility which is defined as the ability to sense and react to opportunities and threats with ease, speed, and agility (Tallon & Pinsonneault, 2011). The agility of a company is not an end in itself, but a means needed to achieve and maintain a competitive advantage in a volatile market (Sherehiy et al., 2007) which will then affect company performance and successfully win the competition (Ashrafi et al., 2019). Previous research has analyzed these influences on a turbulent environment (Ashrafi et al., 2019). However, no previous research has analyzed these influences on a turbulent and uncertain environment due to the Covid-19 pandemic. So, this research analyzes the important role of business analytics capability which ultimately affects performance in the Covid-19 pandemic situation.

[1]First Author and Corresponding Author. Lecturer, Faculty of Economics and Business, Universitas Pelita Harapan, Indonesia [Postal Address: MH Thamrin Boulevard 1100, Klp. Dua, Kec. Klp. Dua, Tangerang, Banten 15811, Indonesia] Email: albert.wanasida@lecturer.uph.edu
[2]Lecturer, Graduate School of Management, Universitas Pelita Harapan, Indonesia. Email: innocentius.bernarto@uph.edu
[3]Lecturer, Faculty of Education, Universitas Pelita Harapan, Indonesia. Email: niko.sudibjo@uph.edu
[4]Lecturer, Faculty of Education, Universitas Pelita Harapan, Indonesia. Email: agozpor@gmail.com

In this paper, we describe two important constructs to explain the mechanisms through which business analytics capability affects organizational agility and performance. Guided by the theory of effective use representation by Sherehiy et al. (2007), in the context of business analytics capability, the quality of information cannot be separated from the effective use of technology and innovation capability. This shows that information quality and innovation capability are obtained if the company is able to use and manage technology effectively. Organizational agility and information systems (IS) are the contemporary key factors for organizations in terms of operational excellence and competitive advantage. Since organizations have to be flexible and proactive against all environmental changes for survival, information flow through the organizations and their environment should be managed properly. Likewise, developing innovation as a skill becomes a powerful tool for expressing agility within the organization, since it invites its leaders and collaborators to question their processes, communications, work dynamics, use of technological resources and customer relationships, as well as to address trends in their environment (Ashrafi et al., 2019). Therefore, this paper examines the important role of information quality and innovation capability in influencing organizational agility during the Covid-19 pandemic.

This study provides a cohesive research model in explaining the important role of business analytics capability, information quality, and innovation capability in influencing agility and performance. More specifically, this study will (1) test a series of hypotheses related to business analytics capability, information quality, innovation capability, organizational agility, and organization performance in special situations, namely the Covid-19 pandemic, and (2) describe the use of Importance-Performance Map Analysis. (IPMA) to identify which constructs are of the highest importance to construct organizational performance. This research examines companies in Indonesia. There are two main reasons for selecting Indonesia for this study: First, the number of positive cases of Covid-19 in Indonesia continues to increase rapidly, until October 2020 as many as 353,750 people were confirmed positive and 12,347 cases were confirmed dead. This is the highest number of deaths in Southeast Asia (WHO, 2020). This clearly has a big impact on companies in Indonesia. Second, based on survey results, it was recorded that 82.85 percent of companies posted a decrease in income due to Covid-19 (Badan Pusat Statistik, 2020). Given the enormous impact during the Covid-19 pandemic, it is important to identify factors that can increase agility and organizational performance.

We organize this paper into six parts. First, this paper starts with an introduction. Second, it is followed by a literature review and hypothesis development. The third section describes the research method. The fourth, fifth, and sixth sections explain the results, discussion, managerial implication, limitation, and future research.

2. Literature Review

2.1. Business Analytics Capability

Business analytics refers to the skills, technologies, and practices for continuous iterative exploration and investigation of past business performance to gain insight and drive business planning. Business analytics is the use of data, information technology, statistical analysis, quantitative methods, and mathematical or computer-based models to help managers gain better insight into their operations, and make better decisions, based on facts (Davenport & Harris, 2007). In the context of information systems, business analytics capability is defined as the business capabilities that support IT (El Sawy & Pavlou, 2012). Business analytics is the process by which businesses use statistical methods and technologies for analyzing historical data to gain new insight and improve strategic decision-making (Wamba et al., 2017). Business analytics is the combination of skills, technologies, and practices used to examine an organization's data and performance as a way to gain insights and make data-driven decisions in the future using statistical analysis (Chen et al., 2012). The goal of business analytics is to narrow down which datasets are useful and which can increase revenue, productivity, and efficiency. (Holsapple et al., 2014). In the context of Covid-19, business analytics capability is needed to make better decisions in an uncertain business environment.

Past research has examined the important role of business analytics. Aydiner et al. (2019) proposed a model that examined the effects of business analytics (BA) adoption on business process performance (BPER) and the mediating role that BPER plays in the relationship between the adoption of BA and firm performance (FP). The results of this empirical study indicated that the adoption of BA positively influenced BPER. There is also a positive relationship between BPER and FP. Finally, the results showed that BPER fully mediated the relationship between BA adoption and FP. Ashrafi and Zare Ravasan (2018) explored the relationship between market orientation (MO), innovation, and market performance. The study also examined the intervening role of IT infrastructure, business analytics (BA) capabilities, and market turbulence in the proposed model. Despite prior studies which postulated innovation performance as the final outcome of MO, this study focused on innovation performance as a mediating outcome which finally leads to market performance. The results showed that managers would be able to realize the paramount role of innovation as an integral part of achieving higher market performance.

Appelbaum et al. (2017) contributed to the literature by discussing the impact of business analytics on managerial accounting from enterprise systems and BI perspectives and by providing the Managerial Accounting Data Analytics (MADA) framework that incorporates balanced scorecard methodology. MADA provides management accountants the ability to utilize comprehensive business analytics to conduct performance measurement and provide decision-related information. With MADA, three types of business analytics (descriptive, predictive, and prescriptive) are implemented into four corporate performance measurement perspectives (financial, customer, internal process, and learning and growth) in an enterprise system environment.

Krishnamoorthi and Mathew (2018) used a business analysis model to identify elements of analytics technology assets and business analytics capability and to understand the mechanism of business value creation using multiple case studies. They captured how analytics resources contribute to business performance by developing operational and organizational performance measures. Business analytics is needed not only in normal situations but also in uncertain situations (Ashrafi et al., 2019). In the Covid-19 pandemic situation which causes uncertainty in the business environment, it requires every company to have business analytics capability. This is important because in the end, it will affect agility and performance which are the basis for companies to survive a pandemic situation.

2.2. Information Quality

DeLone and McLean (1992) argued that Information quality is a measure of the value which the information provides to the user of that information. Information quality is the quality of the content of information systems. It is often pragmatically defined as the fitness for use of the information provided. According to Shen et al. (2017), information quality shows the quality of the output from the information system in the form of reports or data displayed. According to Wang and Strong (1996), the following are the dimensions or elements of information quality: intrinsic − accuracy, objectivity, believability, reputation; contextual − relevancy, value-added, timeliness, completeness, amount of information; representational − interpretability, format, coherence, compatibility; accessibility − accessibility, access security. Information is a vital resource for the success of any organization. According Adinugraha et al. (2021); Lemy et al. (2020) and Sasono et al . (2021) The future of an organization lies in using and disseminating information wisely. Good quality information placed in the right context at right time tells us about opportunities and problems well in advance. Organizations and researchers strive to achieve information quality goals, namely determining the characteristics of information items that are important, or suitable for information consumers (Ashrafi et al., 2019; Dedeoglu, 2019; DeLone & McLean, 2003). For this reason, this study focuses on information output that is precise, accurate, complete, available adequately, and can be relied on by information users (Ashrafi et al., 2019; DeLone & McLean, 2003) which will ultimately affect organizational agility.

Many previous studies have shown the important role of information quality in business decision-making. According Goeltom et al. (2020) and Vizano et al. (2021 the capability and maturity of an organization to manage the quality of its information can mean the difference between success and failure. Information quality is becoming a competitive advantage for many companies. Information is shared amongst various decision-makers within the organization and between supply chain partners not only to bench-mark, amend, or formulate competitive strategies but also to control day-to-day operations and to solve problems on a real-time basis (Sharda et al., 2016).

Bhatt et al. (2010) examined how the flexibility of an organization's IT infrastructure enhanced information generation and dissemination and that this increased their ability to respond to rapidly changing environments. They found that IT infrastructure flexibility was positively related to information generation and dissemination. Moreover, information generation was significantly related to organizational responsiveness. Finally, organizational responsiveness was positively related to the firm's competitive advantage. Quality information obtained from corporate information systems such as enterprise resource planning (ERP) systems has provided extended data storage power management and enhanced computing power (Appelbaum et al., 2017). Thus, it can be concluded that information quality can provide benefits for the company both in the internal and external environment. For this reason, this research can complement a new understanding of information quality related to its effect on organization agility during the Covid-19 pandemic.

2.3. Innovation Capability

Innovation literature claims that innovation is the most fundamental source for a firm's success and survival (Abbing, 2010; Rajapathirana & Hui, 2018). Innovation can only happen if the company has the capacity to innovate (Laforet, 2011). Innovation capability is defined as a firm›s ability to identify new ideas and transform them into new/ improved products, services, or processes that benefit the firm. Increasing a company's ability to innovate means developing the right framework conditions to achieve innovation goals (Lawson & Samson, 2001). Innovation capability is defined as the company's ability to generate, receive, and implement new ideas, processes, products, or services. Innovation capability is defined as continually improving the capabilities and resources of firms for discovering opportunities in order to engage in new product development. Innovation increases the chances to react to changes and discover new opportunities. It can also help foster competitive advantage as it allows organizations to build better products and services for their customers (Wang et al., 2013).

According to Adler (1990), innovation capability is defined as (1) the capacity of developing new products satisfying market needs; (2) the capacity of applying appropriate process technologies to produce these new products; (3) the capacity of developing and adopting new products and processing technologies to satisfy future needs; (4) and the capacity to respond to the accidental technology activities and unexpected opportunities created by competitors. Dekoulou and Trivellas (2017) explored the impact of organizational structure dimensions on innovation performance as well as its implications on business customers' relationship value and financial performance in the business-to-business (B2B) market of the Greek advertising and media industry. Findings showed that training boosts an organization's capacity to innovate, whereas direct supervision as a coordination mechanism significantly restricts this capacity. Innovation performance in the advertising B2B market fosters business customers' relationship value and financial performance, while financial outcomes are also beneficially affected by profitable relationships with customer relationship value.

Many previous studies have analyzed the benefits of innovation capability in companies. Zain et al. (2005) examined the influence of information technology (IT) acceptance on organizational agility. Results showed that actual system or technology usage had the strongest direct effect on organizational agility. Meanwhile, perceived usefulness and perceived ease of use of IT influenced organizational agility indirectly through actual systems or technology use and attitudes towards using the technology. Innovation capability facilitates companies to introduce new products quickly and adopt new systems in the face of ongoing competition (Rajapathirana & Hui, 2018). Other research collaborates on the innovation network, namely product innovation capability, process innovation capability, and absorptive capacity in producing new products (Najafi-Tavani et al., 2018). This study analyzes innovation capability in terms of how well the organization is able to create innovations and new ideas in marketing products/services (Ashrafi et al., 2019; Wang et al., 2015). This is related to the Covid-19 pandemic situation which requires companies to be agile in facing environmental changes, one of which requires innovation capability.

2.4. Organization Agility

Teece et al. (2016) defined agility organizational agility as a company›s ability to rapidly change or adapt in response to changes in the market. Agility is the ability of an organization to renew itself, adapt, change quickly, and succeed in a rapidly changing, ambiguous, turbulent environment. Organizational agility is a way of organizing and working shown to drive top-tier financial performance. (Dubey et al., 2014). Organizational agility revolves around strengthening relationships between managers and direct reports and giving them a working environment to improve collaboration, innovation, and growth-conversations enabled by technology. Further, agile organizations drive strategic business goals in more effective ways that improve margins, predictability, and profitability. (Dubey et al., 2010). From an organizational perspective, agility is the ability to perceive opportunities for innovation and respond to those opportunities and quickly redesign processes to take advantage of market conditions (Darvishmotevali et al., 2020). Agility is the ability to respond quickly to emerging market opportunities. Organizational agility can be defined as the ability of a company to adapt to external and internal changes; rapidly meet customer demands and expectations; lead change improving culture, practices, and outcomes, and maintain a continuous competitive advantage (Ulrich & Yeung, 2019). In facing competition in a special situation, namely the Covid-19 pandemic, it is important to analyze organization agility to gain practical and theoretical understanding that can complement the organization agility literature.

3. Hypothesis Development

3.1. Business Analytics Capability on Information Quality

The effect of business analytics capability on information quality has been analyzed in previous studies (Appelbaum et al., 2017; Ashrafi et al., 2019; Morales-Serazzi et al., 2021). The influence of business analytics capability on information quality shows that business analytics provides management with the ability to utilize comprehensive business analytics to provide information related to decision making (Appelbaum et al., 2017; Morales-Serazzi et al., 2021). Business analytics aims to improve information used in the decision-making process (Fink et al., 2017). Besides, business analytics capabilities are presented to extract the necessary information, create new knowledge and take the best action in responding to market changes (Ashrafi & Zare Ravasan, 2018). Many companies invest considerable resources in developing business analytics capabilities to improve their performance. Business analytics capabilities strongly impact a firm's agility through an increase in information quality. To provide quality information, the company's capability (for example, descriptive, predictive, and prescriptive data analytics; big data from internal and external sources; and financial and non-financial information) needs to be utilized (Appelbaum et al., 2017). Based on these previous studies, it shows the influence of business analytics capability on information quality.

H1: *Business analytics capability significantly influenced information quality.*

3.2. Business Analytics Capability on Innovation Capability

The effect of business analytics capability on innovation capability has been analyzed in previous research (Ashrafi et al., 2019; Duan et al., 2020). Business analytics capabilities strongly impact a firm's agility through an increase in information quality and innovative capability (the organization's ability to carry out innovative practices) (Wang et al., 2015). Previous studies have shown the importance of a company's ability to extract environmental information to reveal new business opportunities and innovate consistently (Ashrafi et al., 2019; Wang & Dass, 2017). The use of proper business analysis allows companies to generate new knowledge and insights for business which will ultimately improve agility and performance (Ashrafi et al., 2019). Based on this explanation, the formulated hypothesis is as follows:

H2: *Business analytics capability significantly influences innovation capability.*

3.3. Information Quality and Innovation Capability on Organizational Agility

The effect of information quality and innovation capability on organization agility has been proven in previous research (Ashrafi et al., 2019; Rasi et al., 2019). Information quality plays a fundamental role in sensing market changes and ensuring proper organizational decision-making throughout the company (Ashrafi et al., 2019; Rasi et al., 2019). The quality of information shows the extent to which an organization can accurately detect changes in the market and environment and prepare a set of appropriate information for the decision-making process (Popovič et al., 2012). Côrte-Real et al. (2017) believed that processing large amounts of information by applying business analytics is one possible way for companies to achieve agility. On the influence of innovation capability on organization agility, innovation capability appears as the main differentiator for gaining and maintaining competitiveness. The use of IT systems not only increases the potential to continue to innovate but also prepares a supportive environment to achieve agility in the organization (Tan et al., 2017). Previous research also shows that innovation ability affects business agility (Ashrafi et al., 2019; Rasi et al., 2019). Based on this explanation, the formulated hypotheses are as follows:

H3: *Information quality significantly influences organization agility.*

H4: *Innovation capability significantly influences organization agility.*

3.4. Organization Agility on Organization Performance

Agility can have a big impact on company success (Ulrich & Yeung, 2019) and even have an influence on company performance (Ashrafi et al., 2019; Côrte-Real et al., 2017). The positive influence of organization agility on organization performance in a very volatile and uncertain environment has been proven in previous research. Big data analytics can provide business value to several stages of the value chain. Big data analytics can create organizational agility through knowledge management and its impact on the process and competitive advantage. We are living in a dynamic world, customers changing their preferences rapidly which enforce organizations to adopt the concept of organization agility to generate positive organization performance. Organization agility is a competitive advantage that can increase organizational performance and creativity (Darvishmotevali et al., 2020). The Covid-19 pandemic situation requires companies to be agile to improve performance and survive the current situation. Based on this explanation, the formulated hypothesis is as follows (see Figure 1):

H5: *Organization agility significantly influences organizational performance.*

4. Research Method

4.1. Sampling and Data Collection

A self-administered questionnaire (SAQ) refers to a questionnaire that has been designed specifically to be completed by a respondent without the intervention of the researchers (e.g. an interviewer) collecting the data. An SAQ is usually a stand-alone questionnaire though it can also be used in conjunction with other data collection modalities directed by a trained interviewer. Online questionnaires are distributed by researchers to leaders or top managers in several companies in several major cities in Indonesia. Data was collected over a three-week period. Before the recipient filled out each item on the questionnaire, they were asked to agree to an ethics clearance. Respondents are willing to answer each question truthfully through control questions. The number of samples in this study was 76 companies in various sectors. The data analysis technique used was SEM-PLS. Therefore, it requires a minimal number of samples. We used G * Power to calculate the sample size based on statistical power. The statistical power value for this sample was 0.95, higher than the minimum value set at 0.8 (Carranza et al., 2020; Hair et al., 2019). Thus, it can be concluded that the sample size has met the criteria.

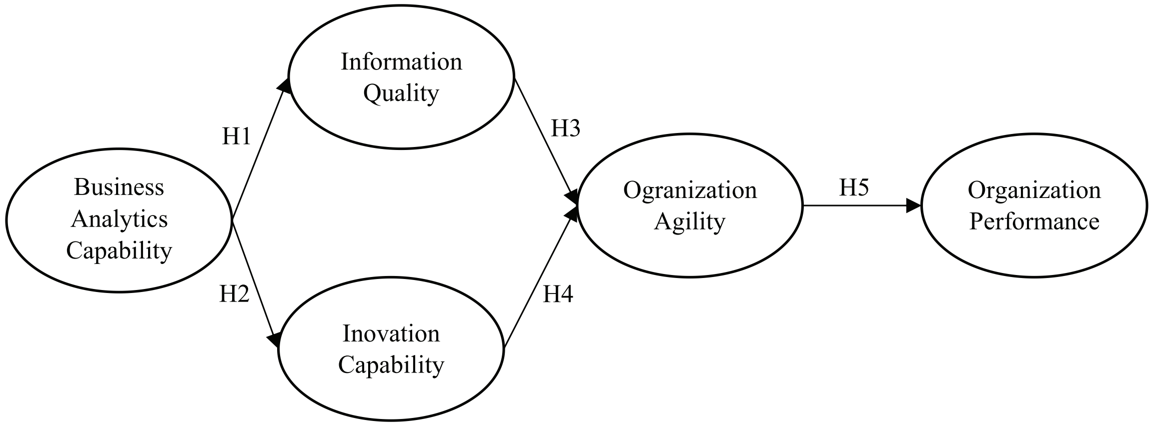

Figure 1: Research Model

The results of the characteristics of the respondents show that there is an almost balanced ratio between the business sectors, namely agriculture (3.9%), property (6.6%), logistics (3.9%), food beverages (5.3%), ICT (5.3%), construction (5.3%), education (3.9%), training consultancy service (18.4%), tourism (1.3%), financial service (13.2%), manufacturing (7.9%), start-up (2.6%), digital (1.3%), and others (2.6%). Most business locations are in Jakarta (69.7%) followed by West Java (11.8%) and other provinces (18.5%). In terms of income, it was - less than IDR 300 million (7.9%), IDR 300 million - IDR 2.5 billion (30.3%), IDR 2.5 billion - 50 billion (36.8), and above IDR 50 billion (25%). This is in line with the length of time the business has been established, which is less than 3 years (25%), 3–5 years (18.4%), 5–10 years (17.1%), and over 10 years (39.5%). These results indicate that the number is balanced based on the length of time the company was founded.

4.2. Research Instruments and Measurements

Constructs were measured using a five-point Likert scale, ranging from 1 = 'strongly disagree' to 5 = 'strongly agree'. Besides, questions related to demographics (field of business, business location, income, and length of business) are also included. We measure modified Business Analytics Capability from previous research (Ashrafi et al., 2019; LaValle et al., 2010) to fit the Covid-19 context. These items ask each respondent to determine the level of analytical capability of their company in the face of the Covid-19 pandemic. Information quality is measured with five items adapted from previous research (DeLone & McLean, 2003) related to information that is precise, accurate, complete, adequately available, and reliable. Innovation capability is measured with four items based on previous research (Ashrafi et al., 2019) regarding how well the organization is able to create innovations and new ideas in marketing products/services. Organization agility is modified from previous research which explains how easily and quickly companies face change (adapted to the Covid-19 pandemic situation) (Darvishmotevali et al., 2020). In measuring organization performance, we use four items namely ROI, market share, sales growth, and customer growth which are modified from previous studies (Ashrafi et al., 2019) and adjusted to the Covid-19 pandemic situation. The items of the questionnaire are shown in Table 1.

4.3. Data Analysis

This study uses the Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis technique because it is a comprehensive multivariate approach to statistical analysis that can simultaneously test every relationship between variables in the conceptual model, including measurement and structural (Hair et al., 2019). The software used is SmartPLS 3.2.7. Based on the PLS-SEM analysis literature, a two-step approach is followed. First, the measurement model is evaluated, and second, the structural model is evaluated (Hair et al., 2019). Two main criteria called reliability and validity have to be achieved in the measurement model before evaluating the structural model. To evaluate the structural model, we have to assess the determination coefficient (R^2), predictive relevance (Q^2), size and significance of path coefficients, and effect sizes (f^2) (Hair et al., 2019). The importance-performance map analysis (IPMA) is a useful analysis approach in PLS-SEM that extends the results of the estimated path coefficient (importance) by adding a dimension that considers the average values of the latent variable scores (performance). The resulting IPMA permits the identification of determinants with relatively high importance and relatively low performance. The IPMA was tested to identify the

Table 1: The Result of the Measurement Model

Construct/Item	Loading	Cronbach' Alpha	Dijkstra–Henseler's rho (rA)	CR	AVE
Business Analytics Capability		0.883	0.886	0.914	0.681
Organizations predict and prepare for the Covid-19 pandemic by proactively evaluating potential tradeoffs	0.797				
Decision making during the Covid-19 pandemic is based on a rigorous analytical approach (e.g., quantitative modeling, simulation)	0.783				
Organizations are able to manage, share and collect data across departments or business units	0.832				
The ability of business information and business analysis during the Covid-19 pandemic was able to differentiate us from other companies in the industry	0.849				
Improving information and analytical capabilities is the top priority during the Covid-19 pandemic	0.863				
Information Quality		0.943	0.945	0.956	0.814
Every piece of information in the organization is made available on time.	0.885				
Every piece of information in the organization is accurately available.	0.914				
Every piece of information in the organization is completely available.	0.897				
Any information in the organization is sufficiently available.	0.902				
Every piece of information in the organization is reliable.	0.912				
Innovation Capability		0.847	0.847	0.897	0.686
Innovation in managerial and business processes	0.813				
Continuously improving the quality of products and services	0.786				
Developing and adopting new technologies that enhance market offerings	0.862				
Developing new products and services with the latest technology	0.849				
Organizational Agility		0.888	0.892	0.915	0.643
Responsive in responding to changes in aggregate consumer demand during the Covid-19 pandemic	0.902				
Products or services in accordance with customer needs during the Covid-19 pandemic	0.793				
Responsive to new products or services launched by competitors during the Covid-19 pandemic	0.793				
Adjust (i.e., expand or reduce) the variety of products/services available for sale during the Covid-19 pandemic	0.817				
Responsive in adopting new technologies to produce better, faster, and cheaper products and services during the Covid-19 pandemic	0.755				

(*Continued*)

Table 1: (Continued)

Construct/Item	Loading	Cronbach' Alpha	Dijkstra–Henseler's rho (rA)	CR	AVE
Change suppliers to get lower costs, better quality, or better delivery times.	0.741				
Organization Performance		0.938	0.949	0.956	0.843
The company's Return on Investments (ROI) has increased during the Covid-19 pandemic	0.941				
Our company's profit growth has increased during the Covid-19 pandemic	0.942				
The revenue (sales) of our company continues to grow during the Covid-19 pandemic	0.907				
Our company's new customers continue to grow during the Covid-19 pandemic	0.881				

Notes: CR: composite reliability; AVE: average variance extracted.

performance of independent constructs (organization performance) and identify constructs that have high relative importance to the target construct (dependent construct) (Ringle & Sarstedt, 2016).

5. Results

5.1. Measurement Model

The first step in PLS-SEM is the evaluation of a measurement model. In evaluating the measurement model, we first test the reliability of the measurement scale for each construct. To assess the individual reliability of the item, loadings of the indicators on each construct were checked. Factor loading is basically the correlation coefficient for the variable and factor. Factor loading shows the variance explained by the variable on that particular factor. In the SEM approach, as a rule of thumb, 0.708 or higher factor loading represents that the factor extracts sufficient variance from that variable. (Hair et al., 2019). In this case, all loadings, except for two items of organization agility were greater than 0.708. Therefore, it is necessary to verify the results of other measurement indexes for the constructs of these items (Hair et al., 2019). To assess the individual reliability of each construct, Composite Reliability (CR) and Dijkstra-Henseler rho (ρA) were calculated. The results show that the CR value is greater than 0.7 for all constructs (Nunnally & Bernstein, 1994). Furthermore, the Dijkstra-Henseler rho (ρA) results exceeded 0.7 in all constructs, indicating its reliability (Hair et al., 2019). Table 1 shows the high level of internal consistency in each construct.

Convergent validity takes two measures that are supposed to be measuring the same construct and shows that they are related. The next step in the measurement model is to test the convergent validity that is reviewed by using the average variance extracted (AVE) which must be greater than 0.5 (Fornell & Larcker, 1981). AVE is a measure of the amount of variance that is captured by a construct in relation to the amount of variance due to measurement error. The results showed that all AVEs for each construct were greater than 0.5 which had a value of 0.643–0.843. Then, the significance of each loading was determined using the bootstrap resampling procedure (5,000 subsamples of the original sample size) to obtain the *t* statistical value (Hair et al., 2019). The results showed that all loadings were obtained significantly with a confidence level of 99.9%.

The next step is to evaluate discriminant validity. To establish discriminant validity, you need to show that measures that should not be related are in reality not related. The average variance extracted has often been used to assess discriminant validity based on the following "rule of thumb": the positive square root of the AVE for each of the latent variables should be higher than the highest correlation with any other latent variable. The criterion of Fornell-Larcker (1981) has been commonly used to assess the degree of shared variance between the latent variables of the model. The results obtained using the Fornell-Larcker criterion show that the square root of each AVE construct value has a higher value than the construct correlation with other latent variables (Fornell & Larcker, 1981). This means that the value of the AVE construct has a higher value than the correlation construct with other latent variables. Discriminant validity was also analyzed by Heterotrait-Monotrait (HTMT) evaluation. The HTMT ratio of correlations (HTMT) is a new method for assessing discriminant validity in partial least squares structural equation modeling, which is one of the key building blocks of model evaluation Using the HTMT as a criterion involves comparing it to a predefined threshold. If the value of the HTMT is higher than this threshold, one can conclude that there is a lack of discriminant validity. Some authors suggest a threshold of 0.90 (Henseler et al., 2015). Other criteria set a value below 0.85 (Hair et al., 2019). In this study, the value obtained is still below the cut-off value which shows good evidence of validity (see Table 2).

5.2. Structural Model

Before analyzing the structural model, collinearity must be checked to ensure there is no bias in the regression results. Multicollinearity (also collinearity) is a phenomenon in which one predictor variable in a multiple regression model can be linearly predicted from the others with a substantial degree of accuracy. Multicollinearity reduces the precision of the estimate coefficients, which weakens the statistical power of your regression model. Variance inflation factor (VIF) is a measure of the amount of multicollinearity in a set of multiple regression variables. A rule of thumb commonly used in practice is if a VIF is > 10, you have high multicollinearity (Hair et al., 2019). The results show that there is no collinearity problem because the VIF value is below the set limit (see Table 3).

Next is to test the structural model. The bootstrap procedure uses 5,000 iterations to evaluate the significance of indicators and path coefficients (Chin et al., 2008). The first step before testing the hypothesis is an assessment of the quality of the model. The criteria used are coefficient of determination (R^2), effect size (f^2), cross-validated redundancy (Q^2), and path coefficient (Hair et al., 2019). The R^2 criteria are 0.75 (substantial), 0.50 (moderate), and 0.25 (weak) for all endogenous structures. The results showed R^2 for information quality is 0.325, R^2 for innovation capability is 0.414, R^2 for organization agility is 0.636, and R^2 for organization performance is 0.173. This shows that each of these constructs is influenced by exogenous constructs with

Table 2: Discriminant Validity

	Constructs	**1**	**2**	**3**	**4**	**5**
Fornell-Larcker criterion	1. Business Analytics Capability	0.825				
	2. Information Quality	0.570	0.902			
	3. Innovation Capability	0.643	0.517	0.828		
	4. Organization Agility	0.616	0.681	0.707	0.802	
	5. Organization Performance	0.280	0.368	0.372	0.416	0.918
Heterotrait-Monotrait Ratio (HTMT)	1. Business Analytics Capability					
	2. Information Quality	0.624				
	3. Innovation Capability	0.735	0.572			
	4. Organization Agility	0.691	0.738	0.805		
	5. Organization Performance	0.303	0.388	0.418	0.449	

Note: The square root of AVEs are shown diagonally in bold.

Table 3: Structural Model Evaluation

Relationships	**β**	**Confidence Interval (95%)**	**Variance Explained (R^2)**	**R^2 Adjusted**	**Predictive Relevance (Q^2)**	**Effect Size (f^2)**	**Confidence Interval (95%)**	**VIF**
BAC → IFQ	0.570	[0.403; 0.717]	0.325	0.316	0.255	0.482	[0.194; 1.055]	1.000
BAC → INC	0.643	[0.477; 0.775]	0.414	0.406	0.263	0.705	[0.295; 1.503]	1.000
IFQ → OAG	0.431	[0.257; 0.570]	0.636	0.626	0.366	0.374	[0.117; 0.795]	1.364
INC → OAG	0.485	[0.339; 0.637]				0.473	[0.191; 0.973]	1.364
OAG → OPF	0.416	[0.263; 0.570]	0.173	0.162	0.130	0.209	[0.074; 0.481]	1.000

Notes: n = 5,000 subsample; VIF: variance inflation factor; BAC: business analytics capability IFQ: information quality; INC: inovation capability; OAG: organization agility; OFF: organization performance.

Table 4: Results of Hypothesis Testing

Hypothesis/Relationships	*β*	*T* value	Confidence interval (95%)	Supported
H1. BAC → IFQ	0.570	6.075*	[0.403; 0.717]	Yes
H2. BAC → INC	0.643	6.974*	[0.477; 0.775]	Yes
H3. IFQ → OAG	0.431	4.532*	[0.257; 0.570]	Yes
H4. INC → OAG	0.485	5.243*	[0.339; 0.637]	Yes
H5. OAG → OPF	0.416	4.402*	[0.263; 0.570]	Yes

Notes: n = 5,000 subsample; *$p < 0.001$; BAC: business analytics capability IFQ: information quality; INC: inovation capability; OAG: organization agility; OFF: organization performance.

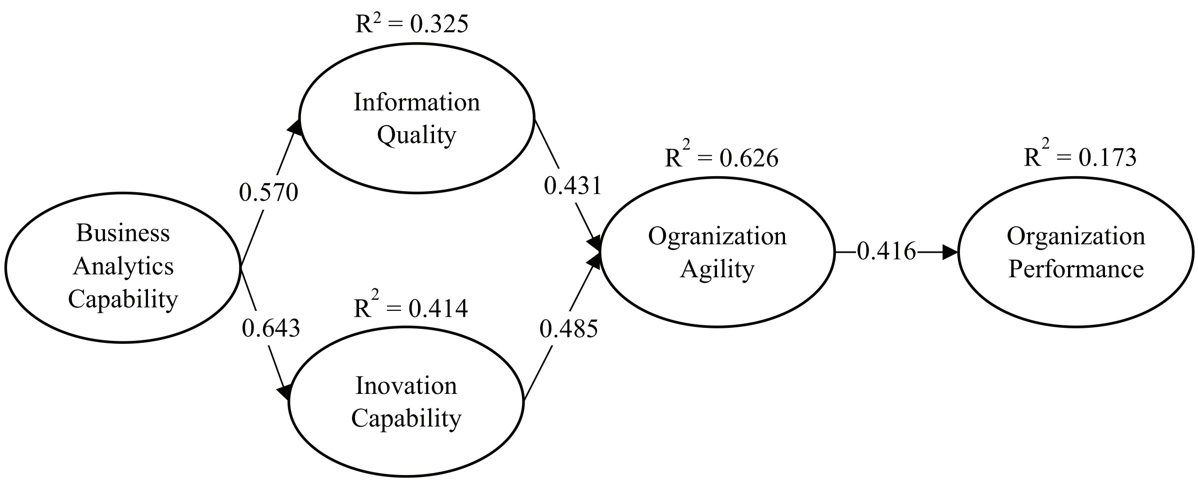

Figure 2: Result Model

moderate criteria, except for organization performance with weak criteria.

The effect size for each path can be determined by calculating f^2. The effect size criteria are 0.02 (small), 0.15 (moderate), and 0.35 (large) (Hair et al., 2019). Each path shows a strong influence unless the influence of organization agility on organization performance is in moderate criteria (0.209). The biggest effect size is the influence of business analytics capability on innovation capability (0.705). Furthermore, to conclude the evaluation of the structural model, the current study tested the predictive relevance model using Stone - Geisser's Q^2 (Hair et al., 2019). The results show that all Q^2 values are above zero (see Table 3), which indicates that the model has acceptable predictive power.

The next step is to test the hypothesis. The results of hypothesis testing are presented in Table 4. Business analytics capability has a significant effect on information quality ($\beta = 0.570$, $t = 6,075$) and innovation capability ($\beta = 0.643$, $t = 6,974$), so that H1 and H2 are accepted. Information quality has a significant effect on organization agility ($\beta = 0.431$, $t = 4.532$). Innovation capability also has a significant effect on organization agility ($\beta = 0.485$, $t = 5,243$), supporting H3 and H4. Finally, organization agility has a significant effect on organization performance ($\beta = 0.416$, $t = 4.402$) so that H5 is accepted. These results are shown in Table 4 and Figure 2.

5.3. Impact-Performance Map Analysis

Importance-Performance Map Analysis (IPMA) for construct organization performance is shown in Table 5. IMPA combines PLS-SEM estimates, indicating the importance of an exogenous construct›s influence on another endogenous construct of interest (target construct). The resulting IMPA permits the identification of determinants with relatively high importance and relatively low performance. These become major and high priority improvement areas with the goal to increase the performance of the selected key target construct in the PLS path model (Ringle & Sarstedt, 2016). The target construct that was tested was organization performance. Among all the constructs, organizational agility is of higher importance (0.626) than the others. Thus, to improve organization performance, aspects related to

Table 5: Importance Performance Map of the Target Construct Organization Performance

Constructs	Organization Performance	
	Important	Performance
1. Business Analytics Capability	0.232	72.721
2. Information Quality	0.179	63.940
3. Innovation Capability	0.202	78.303
4. Organization Agility	0.416	76.069

organization agility must be prioritized because these aspects have the greatest importance and performance in the average performance value of other constructs.

6. Discussion

The results show that business analytics capability affects information quality and innovation capability which is in line with previous research (Ashrafi et al., 2019). The influence of business analytics capability on information quality shows that business analytics provides management with the ability to utilize comprehensive business analytics to provide information related to decisions (Appelbaum et al., 2017; Morales-Serazzi et al., 2021). To provide quality information, the company's capability (for example, descriptive, predictive, and prescriptive data analytics; big data from internal and external sources; and financial and non-financial information) needs to be utilized (Appelbaum et al., 2017). This proves that business analytics capability is a determinant of information quality. The better the company's capability in analyzing the business environment, the better it can determine quality information. Analyzing information more often than not increases efficiency, but also helps identify new business opportunities that may have been otherwise overlooked, such as untapped customer segments. In doing so, the potential for growth and profitability becomes endless and more intelligence-based. In the context of the Covid-19 pandemic, companies that have a high capability in analyzing the uncertainties related to the pandemic will be able to provide quality information in decision making. This is related to uncertainty that can affect company creativity (Darvishmotevali et al., 2020). Thus, this research provides new knowledge that business analytics capability can affect information quality in uncertain conditions such as the Covid-19 pandemic. The higher the company's business analytics capability in analyzing the business environment in the Covid-19 pandemic situation, the more it will affect information quality. Thus, there is a strong link between business analytics and information quality.

The results showed that business analytics capability had a significant effect on innovation capability which was in line with previous research (Ashrafi et al., 2019; Duan et al., 2020). Complementing previous research, this effect also applies to the Covid-19 pandemic situation. The Covid-19 pandemic is causing uncertainty in the business environment which demands careful business analytics capability to deal with this situation. Data-driven decisions and analytics capabilities are particularly valuable to organizations in terms of fostering process innovation. Business analytics capability in the Covid-19 pandemic situation influences the company's innovation capability. Uncertainty causes companies to be more sensitive to increase their innovation. Organizational creativity and innovation depend on the willingness of individuals to endure uncertainty (Courvisanos & Mackenzie, 2014). The results of this study provide new knowledge regarding the effect of business analytics capability on innovation capability in the Covid-19 pandemic situation. The higher the company's business analytics capability in analyzing the business environment in the Covid-19 pandemic situation, the more it will affect innovation capability.

The findings reveal that information quality and innovation capability are not only influenced by business analytics capability but also clearly inform their impact on organization agility. The results of this study are in line with previous research which shows that information quality and innovation capability affect organization agility (Ashrafi et al., 2019; Rasi et al., 2019). The rapidly changing global business environment coupled with unprecedented technological advances forces companies to become more agile in identifying and responding to the evolving needs and wants of customers (Aydiner et al., 2019). This is what allows the company to further improve information quality and innovation capability. Although information quality and innovation capability have been discussed extensively in previous research, to the best of our knowledge, this current research is the first study to theoretically argue that information quality and innovation capability can improve organization agility during the Covid -19 pandemic.

The positive influence of organizational agility on organizational performance in a very volatile environment is in line with previous research (Ashrafi et al., 2019). At its core agility is a decision-making and decision implementation framework. It is based on the assumption that individuals, teams, and organizations which are capable of making decision faster of higher quality and implement them in a timelier manner reach a higher performance level than their less agile peers. Over the long run, a higher level of agility translates into a competitive advantage. When companies face several difficulties in a business environment that requires a very fast response, organization agility is a competitive advantage that can increase organizational performance and creativity (Darvishmotevali et al., 2020). This influence also applies to the conditions of the Covid-19 pandemic. The results of this study prove that organization agility has a significant effect on organization performance in conditions of uncertainty, namely the Covid-19 pandemic. This influence is also supported by the results of IPMA testing which show that aspects related to organization agility must be prioritized because these aspects have the greatest importance and performance in the average performance value of other constructs. These results complement previous research which shows that companies with higher agility in responding to environmental changes such as the Covid-19 pandemic will have higher performance than others.

7. Conclusion and Limitations

The results of this study contribute to an understanding of how superior business analytics capability in a company in a Covid-19 pandemic situation can increase information quality and innovation capability. On the impact of information quality, it is clear that high-quality information obtained from business analytics will help managers to understand the current state of business (the Covid-19 pandemic) and, more importantly, recognize the threats and business opportunities that exist due to these conditions. In dealing with uncertainty, managers must be able to pay attention to, interpret, and learn about the business environment related to the competitive, market, and technological environment (Darvishmotevali et al., 2020). With this capability, it will provide information in making plans to improve company agility and performance which is useful in facing current and future competition. Without having business analytics capability, the chances of successfully competing with competitors can drop dramatically.

In terms of the influence on innovation capability, it is important to improve business analytics capability by developing the skills and abilities of managers in business analysis, so that they can contribute to increasing innovation capability. This process will help managers to be productive today, plan ways to continue productive tomorrow, and help the organization to prove its effectiveness and creativity in the future (Darvishmotevali et al., 2020). In the conditions of the Covid-19 pandemic, if uncertainty is seen as an opportunity, managers can face uncertainty by implementing innovative strategic programs and fostering new ideas and innovations. A company that is dynamic and able to deal with uncertain situations will create a dynamic environment that is suitable for innovative actions so that it will affect the agility and performance of the organization.

The results also prove the effect of organizational agility on organization performance. Organizational agility is needed in conditions of uncertainty, especially in the Covid-19 pandemic situation. Agility is the ability of an organization to renew itself, adapt, change quickly, and succeed in a rapidly changing, ambiguous, turbulent environment. The influence of organizational agility on organizational performance is stronger in the context of a very turbulent environment where companies face some difficulties in forecasting quickly (Ashrafi et al., 2019). For this reason, companies need to restructure their organizations to deal with uncertainty (Darvishmotevali et al., 2020). This allows companies to act with agility to identify threats and challenges, make decisions, and respond quickly to the COVID-19 pandemic situation. Today, companies must think of ways to make their processes more flexible. Organizational agility is a core differentiator in today's rapidly changing business environment. One important aspect of organizational agility is responsiveness (Darvishmotevali et al., 2020). Responsiveness is needed to deal with the current pandemic conditions because responsiveness involves taking appropriate and quick action in response to opportunities and threats. Therefore, the responsiveness aspect of organization agility needs attention to improve organization performance during the Covid-19 pandemic.

There are several limitations that must be acknowledged. First, the results of the R^2 test on organization performance show a value that is not large, which means that there are other factors that need to be tested in predicting organizational performance. Future research is expected to be able to analyze other factors that affect organization performance during the Covid-19 pandemic. Second, the business fields are not fully explored in this research. Results may vary based on the company's line of business. For this reason, future research is expected to be able to analyze certain business fields. Third, this research is limited to companies in a developing country, Indonesia. Results will differ in other countries. The context of a country can also be extended to other countries to compare business capacity in supporting organization agility and performance during the Covid-19 pandemic.

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