




“Measuring innovation capability and its effects on financial performance using companies’ annual reports”

AUTHORS	M. Elfan Kaukab  
ARTICLE INFO	M. Elfan Kaukab (2024). Measuring innovation capability and its effects on financial performance using companies’ annual reports. <i>Problems and Perspectives in Management</i> , 22(3), 134-145. doi: 10.21511/ppm.22(3).2024.11
DOI	http://dx.doi.org/10.21511/ppm.22(3).2024.11
RELEASED ON	Tuesday, 16 July 2024
RECEIVED ON	Wednesday, 01 May 2024
ACCEPTED ON	Tuesday, 25 June 2024
LICENSE	 This work is licensed under a Creative Commons Attribution 4.0 International License
JOURNAL	"Problems and Perspectives in Management"
ISSN PRINT	1727-7051
ISSN ONLINE	1810-5467
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”



NUMBER OF REFERENCES

37



NUMBER OF FIGURES

0



NUMBER OF TABLES

10

© The author(s) 2024. This publication is an open access article.



BUSINESS PERSPECTIVES



LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sумы, 40022, Ukraine
www.businessperspectives.org

Received on: 1st of May, 2024

Accepted on: 25th of June, 2024

Published on: 16th of July, 2024

© M. Elfan Kaukab, 2024

M. Elfan Kaukab, Ph.D., Dean,
Department of Management,
Economics and Business Faculty,
Universitas Sains Al-Qur'an [University
of Al-Qur'an Sciences], Indonesia.



This is an Open Access article,
distributed under the terms of the
[Creative Commons Attribution 4.0
International license](https://creativecommons.org/licenses/by/4.0/), which permits
unrestricted re-use, distribution, and
reproduction in any medium, provided
the original work is properly cited.

Conflict of interest statement:

Author(s) reported no conflict of interest

M. Elfan Kaukab (Indonesia)

MEASURING INNOVATION CAPABILITY AND ITS EFFECTS ON FINANCIAL PERFORMANCE USING COMPANIES' ANNUAL REPORTS

Abstract

Companies try to survive and gain competitive advantage by leveraging their innovation capabilities, which need to be more accurately measured through company annual reports to provide valuable insights for investors and stakeholders. The study aims to analyze how innovation capability can be understood using innovative textual analysis based on linguistic cues to assess the level of a company's innovation capability using secondary data from companies' annual reports and then validated by empirical tests. The study surveyed 30 companies listed on the Indonesian Stock Exchange from various sectors and industries and applied panel data regression with a five-year time series (2018–2022). Innovation capability was an independent variable, measured by textual analysis approach, and return on assets (ROA) and return on equity (ROE) were dependent variables. Descriptive statistics showed no significant differences in innovation capability, ROA, and ROE across sectors. Correlation analysis revealed no significant association between company age and these variables. Panel data regression confirmed that innovation capability positively influences ROA (p -value 0.078) and ROE (p -value 0.035). Notably, the impact of innovation capability on ROA increased during and after the COVID-19 pandemic, highlighting its growing importance in financial performance during challenging times.

Keywords

Indonesia, profitability, regression, relationship, assets, pandemic, investors, shareholders

JEL Classification

O31, M21, G32

INTRODUCTION

Innovation is one of the keys to an organization's success in surviving, achieving profits, and ultimately developing through sustainable competitive advantage (Chatterjee et al., 2023). However, innovation is not accessible, and companies face various obstacles in producing innovation in their business (Forsman, 2021). Some innovations have high failure characteristics, requiring significant investments and high precision (Rhaiem & Amara, 2021). Studies estimate the risk of failure of an innovation project in a company to range between 40-80% (Chatterjee et al., 2024).

Even though there is a huge risk of failure, shareholders consider it essential for the company to innovate. The more diverse the shareholders of a company, the more the company is encouraged to innovate (Wang et al., 2021). Shareholders in high-tech companies strongly encourage the implementation of innovation (Chen et al., 2022). Innovation has become a new awareness for investors and essential for other stakeholders who expect companies to contribute to various social and environmental aspects.

Companies must possess innovation capability to produce successful innovations both technically and marketingly (Mikalef et al., 2020). From an investor's perspective, they must know how to recognize

whether a company has high innovation capabilities. This information must be extracted from annual reports, which are the primary source for shareholders when making investment decisions in a company. Unfortunately, this method is less explored in contemporary research, which uses primary data through surveys to measure a company's innovation capabilities. This survey has a representativeness problem because it requires a sample understanding of innovation issues, even though this knowledge is generally found in the company's top managers. As a result, many studies rely on MSMEs, which are not too large and complex compared to large companies (Saunila, 2020). Accurately measuring innovation capabilities in large companies is still a research gap that needs to be clarified.

1. LITERATURE REVIEW AND HYPOTHESES

Innovation capability is the skills and knowledge needed to absorb, master, and improve existing technologies and create new ones (Zastempowski, 2022). It includes skills and abilities to improve existing products and technologies while creating new ones by turning knowledge into products and processes (Park et al., 2021). Companies with high innovation capabilities reflect the continuous development of innovation from the creation, transformation, and application of knowledge (Hernandez-Perlines et al., 2021). The ultimate goal of innovation capability is consumers because the skills and competencies are directed at efforts to meet market needs through new products, technologies, or processes that are absorbed, dominated, enriched, or created (Gohr et al., 2022).

The innovation capability model implies that this capability has two components: a technological component and a business component. The technological component includes development and operational capabilities, while the business component includes management and transaction capabilities (Leo et al., 2022). A company must master these four capabilities to produce an innovative performance that translates the new aspects developed and operationalized into something that generates profits.

The method commonly used to measure innovation capability is distributing a Likert scale questionnaire, which company representatives will fill out (Sepúlveda & Zúñiga Collazos, 2023). The weakness of this method is that respondents are generally not representative of the company, especially for large companies. In companies like this, knowledge about overall innovation capabilities will lie with top managers who are challenging

to reach and ask for their willingness to fill out a questionnaire. As a result, most studies applying this method use small and medium-sized companies, making it possible to obtain representative samples. Large companies need to be researched more deeply regarding innovation capabilities because the innovations they produce are generally significant for the market and have the potential to change existing competition rules.

Studies with different measurements utilize fuzzy logic to transform limited, subjective, and scarce information about companies' innovation capabilities (Velazquez-Cazares et al., 2021). This study uses qualitative information obtained directly and secondary data.

Several studies use a company's annual reports as information on innovation capabilities. Using textual information analysis, Yuan et al. (2022) used annual reports as a variable that can influence innovation investment in peer companies in the same industry. Ren and Li (2022) employed textual analysis of annual reports to determine a company's level of digital transformation, which was then regressed against green technology innovation to predict accounting-based performance (ROA and ROE). Annual reports are essential because they are instruments stakeholders, especially investors and analysts, use in assessing companies (Bhuyan et al., 2023).

The drawback of the above approach is that it measures information quantitatively. Ren and Li (2022) determine the level of digital transformation based on the frequency of the appearance of specific keywords in annual reports. Frequency is less reliable because companies often repeat what was written in last year's report and often express a concept as rhetoric, namely to sweeten the report, rather than as factual information whose

truth can be revealed (Jian et al., 2024). Alduais (2022) even showed that companies with poor performance reveal more keywords, while companies with good performance reveal information effectively and concisely. Meanwhile, the concept of annual report tone tends to only produce binary information in the form of positive (optimistic) and negative (pessimistic) tones regarding a concept (Hossain et al., 2020), which means it is similar to the concept of sentiment analysis in social media data.

This paper measures innovation capability with a more rigorous and interpretive approach. The use of annual reports to measure innovation capabilities is based on the assumption that annual reports reveal a company's capabilities explicitly and implicitly (Donnelly & Wickham, 2021). The study avoids using frequency as an indicator of innovation capability because of the risk of manipulation (Alduais, 2022). Instead, specific textual characteristics reveal the factuality of the company's innovation capabilities.

Previous research agreed that innovation capability positively and significantly affects company performance. For example, Baláz et al. (2023) found that innovation strategy mediates the relationship between capability development and economic performance for firms-members of the European Structural and Cohesion Funds. Meanwhile, Gošnik et al. (2023) found that innovation capabilities support the use of differentiation strategy and influence the performance of small and medium enterprises in Slovenia. Hanaysha (2020) showed that innovation capabilities, including product, service, process, and marketing innovation, positively affect firm performance in the banking industry in Malaysia. Li et al. (2020) found that the corporate innovation capabilities of China's A-share listed companies positively enhance firm value.

Theoretically, high innovation capability can lead to performance because this capability produces resources that fulfill the characteristics of being valuable, rare, inimitable, and non-substitutable (Teece, 2019). According to the resource-based view, resources that contain these four characteristics are a source of competitive advantage and superior performance (Chatterjee et al., 2024).

Return on assets (ROA) and return on equity (ROE) are indicators of a company's financial performance. ROA is an indication of how much a company's ability to generate profits relative to the amount of assets they own. At the same time, ROE indicates a company's ability to generate profits relative to the amount of capital they hold. Shareholders consider ROE more critical because it reflects the income from their investment in the firms (Neves et al., 2023). ROE shows a company's ability to generate wealth for its investors (Tekin, 2022). On the other hand, ROA is essential for companies because it relies on more stable assets than capital that investors can withdraw at any time (Pennacchi & Santos, 2021).

The relationship between innovation capability and financial performance, such as ROA and ROE, is so strong that these two objective performance indicators are often used to test the validity of measuring innovation capabilities (Donate et al., 2020).

The study aims to analyze how innovation capability can be understood using innovative textual analysis based on linguistic cues to assess the level of a company's innovation capability. To validate the method, two hypotheses advanced, relating the innovation capability with financial performance, measured with return on assets and return on equity. Thus, the study hypothesizes as follows:

H1: Organizational innovation capability positively influences return on assets.

H2: Organizational innovation capability positively influences return on equity.

2. METHODS

2.1. Measures

The study uses a quantitative approach. Data were collected from secondary sources. This paper has three variables: innovation capability, ROA, and ROE. ROA and ROE are indicators of company profitability. Innovation capability is measured by translating the text into an ordinal semantic scale with a score of 1 to 5. The criteria for giving the score are described in Table 1.

Table 1. Scoring scale for innovation capability

Score	Explanation
1	The annual report does not mention the words “innovation” or “innovative,” and the narrative expresses that the company responds to innovations carried out by other parties (for example, information technology innovations) instead of carrying out its innovations.
2	The annual report mentions “innovation” or “innovative” but proves to be just a copy or repetition of what was narrated in the previous year.
3	The annual report mentions the word “innovation” or “innovative” but only as rhetoric, which means it does not provide concrete evidence/specific information or place “innovation” as an essential component of the company. An example of rhetoric is when a company says that they have innovated to maintain the company’s survival but does not explain what form this innovation takes.
4	The annual report places innovation as an essential part of the company, including its vision, mission, code of ethics, organizational culture, business motto, or a particular area of product research and development.
5	The annual report mentions and details what innovations they have carried out throughout the year.

The resulting score is ordinal. Even though it is ordinal, this data can be treated as continuous. A study comparing structural equation analysis procedures using ordinal and interval data did not find significant differences if the data had at least five options (Johal & Rhemtulla, 2023). Only when the number of choices is too small (2, such as yes and no) does the status of the scale, whether ordinal or interval, become significant. Robitzsch (2020) even argues that mathematically ordinal scales can almost always be treated as interval scales. So, like the interval scale, this new scale can be processed with algorithms for interval data such as mean values, standard deviations, and panel data regression analysis.

The dependent variable, profitability, is measured by two indicators: return on assets (ROA) and return on equity (ROE). ROA compares the net profit obtained with the number of assets owned by the company, while ROE compares the net profit with the amount of capital

the company controls from its shareholders. Therefore, ROE is often referred to as an indicator of shareholder wealth.

2.2. Sample and data collection

The population included companies of the Indonesian Stock Exchange (IDX). There are 738 companies registered on IDX as of March 26, 2024. Each company has a profile on the official IDX website. The study randomized the order of company names using the rand between function in Microsoft Excel and sorted the companies that got the smallest random number. A total of 30 companies were taken as research samples (Appendix A). Each company’s website was visited, and information regarding the business sector and industry was collected in the first year it was listed on IDX. Five companies had to be replaced in the data collection process because three went bankrupt, one did not have annual report data, and one had a website that could not be accessed.

Table 2. Example of scoring innovation capability

Score	Criteria	Example
1	There is no such thing as innovation or only responding to innovation	“Training for employees is still online to improve competence and adapt to changes, especially technological innovation.”
2	Copy of previous annual report	In 2018, it was stated that “the company believes that the various investments, innovations, developments, and efficiency measures implemented will ensure business continuity in the future. The company continuously improves the efficiency of various ongoing governance processes while creating various innovations to maintain transparency and accountability in all its business activities.” In 2019, the same narrative was found in the text of the 2019 annual report.
3	Rhetoric	“The investment that the company makes must prepare the company to face challenges, increase productivity, implement innovative best work practices, and take advantage of opportunities to create prosperity for all stakeholders.”
4	Innovation is an integral part of the company.	Creative and innovative behavior is one of the six main behaviors of our people.
5	Real proof of innovation	“The innovations developed by the company throughout 2020 included additional types of cable products following growing demand in the market.”

Company websites were checked, and the company's annual reports from 2018 to 2022 were downloaded. Next, from each annual report, the study collected data on the keyword "innovation" or "innovative" to assess the level of innovation capability possessed by the company. An example of providing an innovation capability score is found in Table 2. ROA and ROE data can be obtained directly from the annual report.

2.3. Data analysis

Before panel data regression analysis, the data were analyzed using descriptive statistics to explain the variables studied briefly. Descriptive statistical analysis consists of average, maximum value, minimum value, and standard deviation.

This paper uses panel data with time series and cross-section data. The time series data referred to is five years (2018–2022). Meanwhile, the cross-section data are from companies registered on IDX. Several methods that can be used to estimate panel data regression models are the Chow, Hausman, and Lagrange Multiplier (LM) Tests. Meanwhile, the models that can occur in panel data regression consist of common effect model (CEM), fixed effect model (FEM), and random effect model (REM).

The common effect model is a simple model that combines all data, both time series and cross sections, and then the model is estimated using ordinary least squares (OLS). This model assumes that the regression results are always valid for the entire research sample.

The fixed effect model is an approach that assumes that individual companies have intercepts that vary between companies (individuals). Constants that remain constant for the entire period in one object are called fixed effects. The Chow test is carried out to determine whether the model has a common or fixed effect with a significance level of 5%. If the test results show the probability value is below 0.05, the study rejects H_0 or accepts H_1 , which means that a fixed effect model is used. Conversely, if the probability value is above 0.05, the data are a common effect model. If the Chow test results obtained are a fixed effect model, then the next stage is to carry out the Hausman test.

The random effect model can be used to overcome the weaknesses of the fixed effect model. The random effect model uses residuals, which are thought to have a relationship between individuals and between times. Therefore, the random effect model (REM) assumes that each individual (firm) has a different intercept and is a random variable. It uses generalized least squares (GLS) in the estimation technique. The Hausman test is carried out to select the best model between the fixed effect and random effect models. If the probability value is below 0.05, the study rejects H_0 , which means the fixed effect model. On the other hand, if the probability value is above 0.05, the study rejects H_1 or accepts H_0 , which means a random effect model.

If, based on a series of model tests, the best model is the random effect model, then statistical assumption analysis is no longer needed. On the other hand, if one obtains a fixed effect or common effect, it is necessary to carry out a multicollinearity and a heteroscedasticity test. In the case of this analysis, the multicollinearity test is not necessary because there is only one independent variable, namely innovation capability.

3. RESULTS

Table 3 shows descriptive statistics for the 30 companies. The sectors with the most representatives are non-primary consumer goods, finance, and industrial, each with six companies. One-way ANOVA was carried out to see differences between sectors in innovation capability, ROA, and ROE, but none of the ANOVAs were significant, indicating no differences in innovation capability, ROA, and ROE between business sectors.

The company's age, calculated from when it was registered as a member of the Indonesian Stock Exchange, varies significantly, with a minimum of three and a maximum of 42 years. The average company age is 19.3 years. Table 4 shows the age distribution of companies. Correlation analysis was carried out to check an association between age and innovation capability, ROA, and ROE. The results do not show a significant correlation, indicating that age does not significantly influence the company's innovation capability, ROA, or ROE.

Table 3. Company profile

Sector	Industry (n)	Frequency (N)
Raw goods	Containers and packaging (1)	2
	Metals and minerals (1)	
Non-primary consumer goods	Automotive components (1)	6
	Clothing and luxury goods (1)	
	Tourism and recreation (1)	
	Household items (1)	
	Department stores (1)	
Specialty retail (1)		
Primary consumer goods	Processed foods (1)	1
Energy	Supporters of oil, gas and coal (2)	3
	Coal (1)	
Infrastructure	Transport infrastructure operators (1)	1
Health	Pharmacy (1)	2
	Health service providers (1)	
Finance	Insurance (1)	6
	Banks (3)	
	Holding and investment companies (2)	
Industry	Electrical (2)	6
	Multi-sector holding company (1)	
	Building products and supplies (2)	
	Machine (1)	
Property and real estate	Real estate managers and developers (1)	1
Technology	Internet applications and services (2)	2

Note: N = 30.

Table 4. Company age distribution

Age range	Frequency (N)
1-10 years old	9
11-20 years old	8
21-30 years old	5
31-40 years old	7
40-50 years old	1

Ideally, the number of data points is $5 \times 30 = 150$ data. However, there are 16 missing data, making a total of 134. Missing data arose because the annual report could not be read. After all, it results from a scan, or the company was not registered on IDX in 2018 or 2019. Table 5 shows the descriptive values. The lowest innovation is 1, and the highest is 5, with a mean value of 3.53 and a standard deviation of 1.33. For the ROA variable, there are only four missing data with a minimum value of -0.68 and a maximum of 0.72 . The mean ROA value is 0.023 , while the standard deviation is 0.147 . It can be seen that the ROA distribution appears balanced between negative and positive

values. For ROE, the minimum value is -1.12 , and the maximum is 0.87 . The mean for ROE is 0.011 , and the standard deviation is 0.276 . The negative values can partly be attributed to the COVID-19 pandemic, although several companies have been showing negative ROA or ROE since 2018.

Panel data analysis was carried out to test the research hypotheses. Analysis with the independent variable ROA begins by carrying out the Chow test (redundant fixed effects test). The results of the Chow test show a significant value ($p < 0.001$), indicating the need to carry out the Hausman test. The Hausman test (correlated random effects test) showed an insignificant value ($p = 0.6316 > 0.05$), indicating the need for a Lagrange Multiplier test. The results of the Lagrange Multiplier test produced a significant value ($p < 0.001$), indicating that the regression model that best suits the characteristics of the existing data is the random effect model. Table 6 shows the results of the random effect model.

Table 5. Descriptive statistics of research variables

Variable	N	Minimum	Maximum	Mean	Std. deviation
Innovation capability	134	1	5	3.53	1.330
ROA	146	-0.68	0.72	0.0231	0.14766
ROE	146	-1.12	0.87	0.0112	0.27685

Table 6. Panel regression results of innovation capability on ROA using random effect model

Variable	Mark	Sig.
Innovation Capability	0.015685	0.0779
Constant	-0.030645	0.4198
R-squared	0.0234	
F-statistics	3.1638	
Durbin-Watson stat	2.0726	
Adjusted R-squared	0.0160	
Probability (F-statistic)	0.0775	

The ROA model does not show autocorrelation because the Durbin-Watson statistic has a value of 2.07 between the minimum value of 1 and the maximum value of 3. The innovation capability coefficient is positive (0.015685), the *t*-statistic is 1.776534, and the *p*-value is 0.0779, indicating a weakly significant value. These results confirm hypothesis 1 that innovation capability has a significant positive effect on ROA.

The *R*-squared value describes how much the independent variable explains the dependent variable. The results show that innovation capability explains ROA with 2.34%. The adjusted *R*-squared is 1.60%, indicating that if the sample were replaced with the population, there would be a decrease in the *R*-squared so that it would only be 1.60%. The model is classified as unfit because it has *F*-statistics that are not too large and are weakly significant. After all, the *p*-value, 0.0775, is more significant than 0.05 but still smaller than 0.10.

The Chow, Hausman, and Lagrange Multiplier tests (using the Bruch-Pagan test) to select the appropriate analysis model for ROE show the same pattern as the results of ROA as the dependent variable, which confirms the use of the random effect model. The Chow test shows a significant value ($p = 0.000$), the Hausman test is not significant ($p = 0.7169 > 0.05$), and the Bruch-Pagan test is significant ($p = 0.000$). Table 7 shows the results of the random effect model for ROE.

Table 7. Panel regression results of innovation capability on ROE using random effect model

Variable	Mark	Sig.
Innovation Capability	0.035938	0.0359
Constant	-0.104948	0.1324
R-squared	0.0332	
F-statistics	4.5416	
Durbin-Watson stat	1.9147	
Adjusted R-squared	0.0259	
Probability (F-statistic)	0.0349	

The *F*-statistic of the ROE model is 4.54, and the probability value is 0.035, which indicates that the model is reasonably fit for explaining ROE using innovation capability. There is no autocorrelation because the Durbin-Watson statistic is 1.9147, which is more than one but less than 3. Innovation capability has a positive coefficient (0.0359) with a *p*-value of 0.0359, so it can be said that there is a positive and significant relationship between innovation capability and ROE. These findings confirm the second research hypothesis that innovation capability significantly and positively affects ROE. In this model, innovation capability explains ROE with 3.32%. Adjusted *R*-squared is close to *R*-squared, which is 2.59%.

The data are divided into three pre-COVID, COVID-19, and post-COVID groups to see whether the COVID-19 pandemic influences the relationship between innovation capability and financial performance. The pre-COVID group is panel data for 2018 and 2019. The COVID group includes panel data for 2020 and 2021. The 2022 data set is analyzed with ordinary regression because it only contains one year, not panel data. The 2022 data represent the post-COVID cohort. Tables 8 and 9 compare the regression results for the pre-COVID, COVID, and post-COVID groups.

Table 8 shows that as the pandemic progresses, the impact of innovation capability on ROA is getting bigger. Before the pandemic, this impact was insignificant, only having a *p*-value of 0.660. During the pandemic, innovation capability has become increasingly important in maintaining ROA. Even though it is still at a not-yet-significant level, the *p*-value during the COVID period has approached significance, namely 0.117. Post-pandemic, the influence of innovation capability was the greatest on ROA, reaching a significant level where the *p*-value this time was <0.050 , namely 0.048.

The pattern of influence of innovation capability on ROE is slightly different from ROA. Regarding ROE, it can almost be said that there was no significant progress when the pandemic occurred. Before the pandemic, the influence of innovation capability on ROE was only 0.161. Even during the pandemic, this effect was only 0.159, a tiny difference. Only after the pandemic did innovation ca-

Table 8. Comparison of panel regression results of innovation capability on ROA with pandemic

Variable	Pre-Covid (2018–2019)		Covid (2020–2021)		Post-Covid (2022)	
	Mark	Sig.	Mark	Sig.	Mark	Sig.
Innovation Capability	0.005	0.660	0.027	0.117	0.069	0.048
Constant	0.004	0.932	-0.077	0.255	-0.179	0.182
R-squared	0.003		0.047		0.146	
F-statistics	0.198	0.657	2.579	0.114	4.289	0.048
Durbin-Watson stat	1.962		1.971		1.774	
Method	REM		REM		OLS	

Note: REM – random effect model, OLS – ordinary least squares.

Table 9. Comparison of innovation capability panel regression results on ROE with the pandemic

Variable	Pre-Covid (2018–2019)		Covid (2020–2021)		Post-Covid (2022)	
	Mark	Sig.	Mark	Sig.	Mark	Sig.
Innovation Capability	0.028	0.161	0.048	0.159	0.036	0.113
Constant	-0.060	0.414	-0.200	0.143	-0.087	0.322
R-squared	0.038		0.036		0.097	
F-statistics	2.016	0.161	1.984	0.165	2.686	0.113
Durbin-Watson stat	1.415		1.867		1.505	
Method	CEM		REM		OLS	

Note: REM – random effect model, CEM – common effect model, OLS – ordinary least squares.

pability's influence on ROE increase, although still at a level that was not yet significant, because it was 0.113, greater than 0.050.

The results of calculations that divide the sample into groups based on the pandemic period reveal that there is generally no significant impact on ROA and ROE. The influence of innovation capability on ROA is getting stronger over time and can be attributed to the pandemic, which encourages innovation to survive. However, this role is not visible in the ROE context. Only after the pandemic did innovation capability significantly affect ROA and ROE.

Regarding more general results for the whole year, innovation capability has a more considerable influence on ROE than on ROA. The influence of innovation capability on ROA is only 0.0779, which is still greater than 0.05, while ROE reaches a significant level, namely $0.0359 < 0.050$. Therefore, innovation capability, which is approached by textual analysis of company annual reports, has a significant effect on financial performance (ROA and ROE), and the COVID-19 pandemic increases the ability of innovation capability to drive ROA, while ROE is affected after the pandemic ends.

Therefore, hypotheses 1 and 2 can be accepted; thus, organizational innovation capability positively influences the return on assets and the return on equity.

4. DISCUSSION

The results show that innovation capability estimated using textual analysis of companies' annual reports significantly influences ROA and ROE. The influence of innovation capability on ROA is only slightly significantly weaker than the influence of innovation capability on ROE. These findings reveal that innovation capabilities can increase shareholder wealth and provide relatively long-term effects. This result differs from the findings of Gošnik et al. (2023), who found that the choice of innovation strategy had no effect on ROE but only had an effect on ROA among MSMEs in Slovenia. However, Quelhas (2021), researching manufacturing companies in Brazil, Russia, India, and China, showed a more decisive influence of innovation on ROE than ROA. A possible explanation is that the effect of innovation capability is more significant on ROE for large companies, while the effect of innovation will be more

toward ROA for MSMEs. This reason makes sense, considering that large companies are more likely to rely on equity to grow than small companies, which rely more on assets.

Another finding is that there is no significant difference in the influence of innovation capability on ROA and ROE before, during, and after the pandemic. This finding aligns with the absence of significant differences between innovation capability, ROA, and ROE before, during, and after the pandemic. Some companies were able to improve their performance and innovation after the pandemic, but others experienced a decline. There were seven companies whose innovation pattern increased during the pandemic and then decreased afterward, and 12 companies experienced a decline in innovation during the pandemic and

then experienced an increase afterward. Four companies experienced continuous improvement from before to after the pandemic, and only one experienced a decline. Four have static conditions, and one is wavy. The remaining one does not have more than one point.

Meanwhile, 11 companies experienced a decrease in ROA/ROE during the pandemic and then increased afterward. Only one company was operating in the health sector, which experienced an increase during the pandemic and then decreased afterward. Most, namely 17 companies, had fluctuating performance patterns during the five years of observation. Further research is needed to understand the factors behind these patterns and whether this finding is affected by the industry level or individual firm characteristics.

CONCLUSION

The paper investigates the relationship between innovation capability, measured through textual analysis of companies' annual reports, and financial performance, specifically ROA and ROE, using panel data regression analysis. Descriptive statistics of 30 companies from various sectors show no significant differences in innovation capability, ROA, and ROE across sectors, and correlation analysis indicates no significant association between company age and these variables. The analysis reveals that innovation capability has a weakly significant positive effect on ROA and a significant positive effect on ROE, with the impact on ROA increasing over time, especially during and after the COVID-19 pandemic. The study concludes that innovation capability significantly influences financial performance, with the pandemic accentuating the role of innovation in driving financial outcomes.

This paper provides two main theoretical contributions. It develops a new way to measure innovation capability using textual analysis of company annual reports, potentially automatable by artificial intelligence in the future, avoiding issues of keyword frequency methods (Alduais, 2022; Jian et al., 2024). Additionally, it introduces a linguistic and semiotic approach to analyzing variables in strategic management (Di Tullio et al., 2020), bridging qualitative and quantitative approaches (Whittle et al., 2023). Practical implications for managers include the necessity of increasing and transparently reporting innovation capabilities to convince shareholders and attract long-term investments (Kim et al., 2019). It emphasizes that all industries need to innovate, and crises can be opportunities for innovation, exemplified by a company achieving high ROA during the pandemic through health industry innovations.

The study acknowledges several limitations, such as the focus on a single independent variable and the reliance on data from Indonesia, which may limit the generalizability of the findings. Future research should include more control variables, collect data from other countries, and use more extended data sets to enhance robustness. Moreover, future studies should move beyond keyword-based analysis to a more holistic approach that captures the broader meaning of the text, aligning more closely with the company's intentions and the researchers' interpretations.

AUTHOR CONTRIBUTIONS

Conceptualization: M. Elfan Kaukab.
 Data curation: M. Elfan Kaukab.
 Formal analysis: M. Elfan Kaukab.
 Funding acquisition: M. Elfan Kaukab.
 Investigation: M. Elfan Kaukab.
 Methodology: M. Elfan Kaukab.
 Project administration: M. Elfan Kaukab.
 Resources: M. Elfan Kaukab.
 Software: M. Elfan Kaukab.
 Supervision: M. Elfan Kaukab.
 Validation: M. Elfan Kaukab.
 Visualization: M. Elfan Kaukab.
 Writing – original draft: M. Elfan Kaukab.
 Writing – review & editing: M. Elfan Kaukab.

REFERENCES

1. Alduais, F. (2022). Textual analysis of the annual report and corporate performance: Evidence from China. *Journal of Financial Reporting and Accounting*. <https://doi.org/10.1108/JFRA-04-2022-0129>
2. Baláz, V., Jeck, T., & Balog, M. (2023). Firm performance over innovation cycle: Evidence from a small European economy. *Journal of Innovation and Entrepreneurship*, 12(1), Article 40. <https://doi.org/10.1186/s13731-023-00298-9>
3. Bhuyan, A. K., Baid, C., Baid, D., & Mishra, M. (2023). Tone, readability, and firm performance: a study of chairman's letter across India and China. In Rajagopal & R. Behl (Eds.), *Paradigm Shift in Business* (pp. 51-75). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-40439-9_3
4. Chatterjee, S., Chaudhuri, R., Mariani, M., & Fosso Wamba, S. (2023). The consequences of innovation failure: An innovation capabilities and dynamic capabilities perspective. *Technovation*, 128, Article 102858. <https://doi.org/10.1016/j.technovation.2023.102858>
5. Chatterjee, S., Rana, N. P., & Dwivedi, Y. K. (2024). How does business analytics contribute to organisational performance and business value? A resource-based view. *Information Technology & People*, 37(2), 874-894. <https://doi.org/10.1108/ITP-08-2020-0603>
6. Chen, W., Zhong, X., & Lv, D. D. (2022). Negative performance feedback, CEO tenure, and punctuated equilibrium innovation. *R&D Management*, 52(3), 564-576. <https://doi.org/10.1111/rdm.12501>
7. Di Tullio, P., Valentinetti, D., Nielsen, C., & Rea, M. A. (2020). In search of legitimacy: A semi-otic analysis of business model disclosure practices. *Meditari Accountancy Research*, 28(5), 863-887. <https://doi.org/10.1108/ME-DAR-02-2019-0449>
8. Donate, M. J., Ruiz-Monterrubio, E., Sánchez De Pablo, J. D., & Peña, I. (2020). Total quality management and high-performance work systems for social capital development: Effects on company innovation capabilities. *Journal of Intellectual Capital*, 21(1), 87-114. <https://doi.org/10.1108/JIC-07-2018-0116>
9. Donnelly, T., & Wickham, M. (2021). Exploring the antecedent resources and capabilities of strategic corporate social responsibility. *Social Responsibility Journal*, 17(7), 985-1006. <https://doi.org/10.1108/SRJ-12-2018-0334>
10. Forsman, H. (2021). Innovation failure in SMEs: A narrative approach to understand failed innovations and failed innovators. *International Journal of Innovation Management*, 25(09), Article 2150104. <https://doi.org/10.1142/S1363919621501048>
11. Gohr, C. F., Scoralick De Almeida Tavares, M., & Morioka, S. N. (2022). Evaluating the innovation capability of cluster-based firms: A graph-theoretic approach. *Journal of Business & Industrial Marketing*, 37(7), 1402-1421. <https://doi.org/10.1108/JBIM-11-2020-0521>
12. Gošnik, D., Kavčič, K., Meško, M., & Milost, F. (2023). Relationship between changes in the business environment, innovation strategy selection and firm's performance: Empirical evidence from Slovenia. *Administrative Sciences*, 13(4), Article 99. <https://doi.org/10.3390/admsci13040099>
13. Hanaysha, J. R. (2020). Innovation capabilities and authentic leadership: Do they really matter to firm performance? *Journal of Asia-Pacific Business*, 21(4), 271-290. <https://doi.org/10.1080/10599231.2020.1824523>
14. Hernandez-Perlines, F., Ribeiro-Soriano, D., & Rodríguez-García, M. (2021). Transgenerational innovation capability in family firms. *International Journal of Entrepreneurial Behavior & Research*, 27(1),

- 1-25. <https://doi.org/10.1108/IJEBR-08-2019-0497>
15. Hossain, M., Raghunandan, K., & Rama, D. V. (2020). Abnormal disclosure tone and going concern modified audit reports. *Journal of Accounting and Public Policy*, 39(4), Article 106764. <https://doi.org/10.1016/j.jaccpubpol.2020.106764>
 16. Jian, J., Yang, F., Liu, M., & Liu, Y. (2024). Cost of equity capital and annual report tone manipulation. *Emerging Markets Finance and Trade*, 60(3), 519-540. <https://doi.org/10.1080/1540496X.2023.2226320>
 17. Johal, S. K., & Rhemtulla, M. (2023). Comparing estimation methods for psychometric networks with ordinal data. *Psychological Methods*, 28(6), 1251-1272. <https://doi.org/10.1037/met0000449>
 18. Kim, H., Park, K., & Roy Song, K. (2019). Do long-term institutional investors foster corporate innovation? *Accounting & Finance*, 59(2), 1163-1195. <https://doi.org/10.1111/acfi.12284>
 19. Leo, R. M., Camboim, G. F., Avila, A. M. S., Reichert, F. M., & Zawislak, P. A. (2022). Innovation capabilities in agribusiness: Evidence from Brazil. *RAUSP Management Journal*, 57(1), 65-84. <https://doi.org/10.1108/RAUSP-02-2021-0019>
 20. Li, Z., Liao, G., & Albitar, K. (2020). Does corporate environmental responsibility engagement affect firm value? The mediating role of corporate innovation. *Business Strategy and the Environment*, 29(3), 1045-1055. <https://doi.org/10.1002/bse.2416>
 21. Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2020). The role of information governance in big data analytics driven innovation. *Information & Management*, 57(7), Article 103361. <https://doi.org/10.1016/j.im.2020.103361>
 22. Neves, M. E. D., Baptista, L., Dias, A. G., & Lisboa, I. (2023). What factors can explain the performance of energy companies in Portugal? Panel data evidence. *International Journal of Productivity and Performance Management*, 72(3), 730-752. <https://doi.org/10.1108/IJPPM-01-2021-0057>
 23. Park, H., Anderson, T. R., & Seo, W. (2021). Regional innovation capability from a technology-oriented perspective: An analysis at industry level. *Computers in Industry*, 129, Article 103441. <https://doi.org/10.1016/j.comp-ind.2021.103441>
 24. Pennacchi, G. G., & Santos, J. A. C. (2021). Why do banks target ROE? *Journal of Financial Stability*, 54, Article 100856. <https://doi.org/10.1016/j.jfs.2021.100856>
 25. Quelhas, F. D. C. (2021). The effect of innovation on the financial performance and export intensity of firms in emerging countries. *Revista de Administração Da UFMS*, 14, 1259-1279. <https://doi.org/10.5902/1983465938078>
 26. Ren, Y., & Li, B. (2022). Digital transformation, green technology innovation, and enterprise financial performance: Empirical evidence from the textual analysis of the annual reports of listed renewable energy enterprises in China. *Sustainability*, 15(1), Article 712. <https://doi.org/10.3390/su15010712>
 27. Rhaïem, K., & Amara, N. (2021). Learning from innovation failures: A systematic review of the literature and research agenda. *Review of Managerial Science*, 15(2), 189-234. <https://doi.org/10.1007/s11846-019-00339-2>
 28. Robitzsch, A. (2020). Why ordinal variables can (almost) always be treated as continuous variables: Clarifying assumptions of robust continuous and ordinal factor analysis estimation methods. *Frontiers in Education*, 5, Article 589965. <https://doi.org/10.3389/educ.2020.589965>
 29. Saunila, M. (2020). Innovation capability in SMEs: A systematic review of the literature. *Journal of Innovation & Knowledge*, 5(4), 260-265. <https://doi.org/10.1016/j.jik.2019.11.002>
 30. Sepúlveda, I. C. Q., & Zúñiga Collazos, A. (2023). Innovation capabilities, innovation strategies and performance: An empirical analysis in SMEs. *Technology Analysis & Strategic Management*. <https://doi.org/10.1080/09537325.2023.2280523>
 31. Teece, D. J. (2019). A capability theory of the firm: An economics and (strategic) management perspective. *New Zealand Economic Papers*, 53(1), 1-43. <https://doi.org/10.1080/00779954.2017.1371208>
 32. Tekin, B. (2022). What are the internal determinants of return on assets and equity of the energy sector in Turkey? *Financial Internet Quarterly*, 18(3), 35-50. <https://doi.org/10.2478/fiqf-2022-0018>
 33. Velazquez-Cazares, M. G., Gil-Lafuente, A. M., Leon-Castro, E., & Blanco-Mesa, F. (2021). Innovation capabilities measurement using fuzzy methodologies: A Colombian SMEs case. *Computational and Mathematical Organization Theory*, 27(4), 384-413. <https://doi.org/10.1007/s10588-020-09321-w>
 34. Wang, R., Ma, S., Xu, X., & Song, P. (2021). Heterogeneous shareholders' participation, COVID-19 impact, and innovation decisions of state-owned firms: Evidence from China. *Sustainability*, 13(8), Article 4406. <https://doi.org/10.3390/su13084406>
 35. Whittle, A., Vaara, E., & Maitlis, S. (2023). The role of language in organizational sensemaking: An integrative theoretical framework and an agenda for future research. *Journal of Management*, 49(6), 1807-1840. <https://doi.org/10.1177/01492063221147295>
 36. Yuan, D., Shang, D., Ma, Y., & Li, D. (2022). The spillover effects of peer annual report tone for firm innovation investment: Evidence from China. *Technological Forecasting and Social Change*, 177, Article 121518. <https://doi.org/10.1016/j.techfore.2022.121518>
 37. Zastempowski, M. (2022). What shapes innovation capability in micro-enterprises? New-to-the-market product and process perspective. *Journal of Open Innovation: Technology, Market, and Complexity*, 8(1), Article 59. <https://doi.org/10.3390/joitmc8010059>

APPENDIX A

Table A1. Sample corporations

	Code	IPO	Sector	Industry
1	DIVA	2018	Technology	Internet Applications & Services
2	EDGE	2021	Technology	Internet Applications & Services
3	LMPI	1994	Non-Primary Consumer Goods	Household Goods
4	SONA	1992	Non-Primary Consumer Goods	Department Stores
5	YPAS	2008	Raw Goods	Containers & Packaging
6	BSSR	2012	Energy	Coal
7	SMSM	1996	Non-Primary Consumer Goods	Automotive components
8	GDST	2009	Raw Goods	Metals and Minerals
9	BBNI	1996	Finance	Bank
10	CCSI	2019	Industry	Electricity
11	BGTG	2016	Finance	Bank
12	MTLA	2011	Property and Real Estate	Real Estate Manager & Developer
13	SILO	2013	Health	Health Service Providers
14	SMRU	2011	Energy	Supporting Oil, Gas & Coal
15	PORT	2017	Infrastructure	Transportation Infrastructure Operator
16	POOL	1991	Finance	Holding & Investment Company
17	TAMU	2017	Energy	Supporting Oil, Gas & Coal
18	DNET	2000	Finance	Holding & Investment Company
19	AHAP	1990	Finance	Insurance
20	BNBR	1989	Industry	Multi-sector Holding Company
21	IKAI	1997	Industry	Building Products & Supplies
22	JGLE	2016	Non-Primary Consumer Goods	Tourism and Recreation
23	CARS	2017	Non-Primary Consumer Goods	Specialty Retail
24	SIDO	2013	Health	Pharmacy
25	IKBI	1991	Industry	electricity
26	BNBA	2006	Finance	Bank
27	BRICK	1982	Non-Primary Consumer Goods	Clothing and Luxury Goods
28	SKLT	1993	Primary Consumer Goods	Processed Foods
29	SPTO	2018	Industry	Building Products & Supplies
30	UNTR	1989	Industry	Machine

Note: IPO = initial public offering.