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Discriminant Function Analysis As a Performance Differentiator of Information and Communication Technology (ICT) Companies Listed In Us Capital Market for the Period 2021-2023

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ABSTRACT: *The technology industry has experienced rapid growth and transformation in recent years, driven by digital innovation and increasing reliance on technology across various sectors. This underscores the importance of the ICT sector in stimulating economic growth and innovation, as well as its significant role in digitalization. Many institutions and researchers have conducted studies to measure the value created by digitalization, but few have emphasized the importance of financial information as a tool for assessing the performance of ICT companies. Therefore, this study aims to evaluate the importance of financial ratios in measuring the performance of ICT companies. This research uses discriminant function analysis to identify the best financial ratios that differentiate the performance of ICT companies based on their credit ratings. The study sample includes 50 US-based companies listed on the US stock market in the ICT group, with 25 companies in each of the Investment Grade and Non-Investment Grade groups. Three financial ratios are most effective in distinguishing performance between these two groups: CFO to Net Sales (X13), Total Debt to Total Assets (X7), and CFO to Current Liabilities (X6). This model has a predictive accuracy of 71.3% during the 2021-2023 period.*

KEYWORDS:– *ICT Company, Digital Economy, S&P Global, Financial Ratios, Discriminant Analysis*

I. INTRODUCTION

The technology industry has experienced rapid growth and transformation in recent years, driven by advances in digital innovation and increasing reliance on technology across various sectors [1]. The global technology industry is undergoing significant development, with emphasis on areas such as artificial intelligence, the Internet of Things, cloud computing, and big data analytics. Additionally, trends such as the rise of e-commerce, electric and autonomous vehicles, cybersecurity, digital health, fintech, sustainability, green technology, as well as data and privacy regulations are also shaping this industry [2], [3]. The significant impact of digitalization stemming from technological innovation and disruption has influenced various fields of life, including business organizations, industry, the economy, and societal well-being [4]. The Bureau of Economic Analysis (BEA) measures the impact of the digital economy by accounting for infrastructure, software, valuable digital services, and e-commerce margins, among other factors. In 2022, the digital economy contributed 10.0% to the Gross Domestic Product (GDP) of the United States. The growth of the digital economy continues to progress rapidly with the emergence of new technologies shaping its course [5].

There has been a consistent increase in internet usage worldwide year after year, in line with technological advancements and population growth. In January 2022, the number of global internet users reached 4.95 billion, a 4% increase compared to the previous year. By January 2023, this figure had risen to 5.25 billion users, representing approximately 64.4% of the world's total population. Future projections indicate that this upward trend will continue, pandemic has provided an extra boost to internet usage. With the adoption of remote work and learning models, as well as increased consumption of digital content, there has been a significant surge in online activity. ICT companies themselves have faced both positive and negative impacts from the COVID-19 pandemic. Some have experienced increased demand for technology and digital services, while others have had to adapt their business models and operations due to the pandemic's effects [7], [8].

The increase in internet usage and the impact of COVID-19 have created opportunities and driven demand for ICT products and services in the United States, spurring innovation and development in this industry. In 2023, the United States held the largest GDP value in the world, significantly higher than the next largest country, China. The United States remained at the top, with an estimated GDP of around US$26.9 trillion, accounting for 25.8% of the total global GDP. On the other hand, China remained in second place, with a projected GDP of around US$17.7 trillion, representing 16.9% of the total global GDP [9].

This significant contribution also reflects the dominance of American companies in the global market, as illustrated by the list of the 100 largest companies in the world by market capitalization in 2022. This list underscores the dominance of American companies, with most of the companies on the list originating from the United States. Four big tech companies, namely Apple, Microsoft, Alphabet, and Amazon, dominated the top ranks [10]. This underscores the importance of the ICT sector in stimulating economic growth and innovation, as well as their significant role in driving the wave of digitalization.

In the context of modern business, the value creation from digitalization processes is often associated with various perspectives, which are frequently evaluated qualitatively by many institutions and academics. Therefore, the emphasis on quantitative assessment, such as using financial ratios as variables to measure the value of digitalization, is still relatively rare [11]. Although qualitative approaches can be effective methods for monitoring long-term growth and innovation in successful ICT companies, these approaches often fall short in accurately identifying financial risks that might lead to failure, such as bankruptcy risks [11]. This is also illustrated by several companies in the United States, which have shown that financial reports have a limited impact on their performance. For example, Amazon reported a net loss of $2.7 billion in 2022, despite having a market capitalization of over $1.4 trillion [12]. However, looking at Dell Technologies, which has a market capitalization of only $35.3 billion, lower than the previous year, the company recorded a profit of approximately $4.9 billion, an increase from the previous year [13].

Despite having a large market capitalization, a company may not necessarily have good financial health. This indicates that a high market capitalization does not always reflect a company's financial well-being but also considers external factors. This situation presents a challenge that must be addressed in this research. Therefore, this study focuses on the financial dimension in evaluating the performance of ICT companies, emphasizing the significance of financial metrics in bankruptcy prevention efforts. By doing so, stakeholders can more precisely identify potential financial risks that could lead to financial failure.

In the context of the ICT industry, where technological changes and market competition are highly dynamic, placing greater emphasis on financial aspects becomes increasingly important. This is necessary to provide clear guidance in achieving strong financial performance in the future, considering the constantly changing market dynamics. Therefore, integrating qualitative measurements, which monitor innovation and adaptability, with quantitative measurements, which assess financial health and operational performance, becomes essential to anticipate financial risks and ensure sustainable business continuity.

This research examines the use of discriminant function analysis to differentiate the performance of information and communication technology companies using financial ratios as predictor variables, through hypothesis testing. It is expected that this research will fill the gap in academic literature regarding the importance of financial ratio analysis in evaluating the performance of ICT companies, aligning with the increasing relevance of ICT companies' roles in the digital economy context.

II.LITERATURE REVIEW

2.1 Theoretical Foundation

2.1.1 Digital Economy

The rapid advancement of technology and the widespread adoption of digital technology have given rise to the digital economy, transforming how businesses operate and reframing traditional industries. The digital economy encompasses various aspects, including e-commerce, digital platforms, online services, and data-driven innovations. It has become a driving force behind economic growth, innovation, and increased productivity in many countries around the world [14], [15]. These advancements have facilitated the smooth flow of information, the expansion of online markets, and the emergence of new business models centered around digital platforms [16]. One of the main drivers of the digital economy is the proliferation of digital platforms, which connect producers, consumers, and service providers in new ways. These platforms enable businesses to reach a global audience, facilitate peer-to-peer transactions, and promote collaborative consumption. Companies like Amazon, Alibaba, Uber, and Airbnb have become prominent examples of digital platforms that have revolutionized their respective industries [17], [18]. Finally, the digital economy strengthens the operations and management of companies' internal digital resources through the utilization of information technology to interact with various stakeholders, with the aim of building inclusive digital information-sharing platforms [19].

2.1.2 S&P Global Ratings

Credit ratings are assessments made with information related to credit risk. Credit ratings are a projective assessment of the relative creditworthiness of an issuer. They provide a widely used and transparent global language for investors to form views and compare the relative likelihood of whether an issuer can pay its debts fully and on time [20]. Credit ratings facilitate the process of issuing and purchasing bonds and other debts.

By providing an efficient, broad, and long-lasting measure of relative credit risk, credit ratings are applied to bond issuers, debt securities, and bank borrowers [21].

There are several well-known and trusted credit rating agencies, including S&P Global, which provides credit ratings to companies and governments. Integrity, innovation, and collaboration are at the core of this company's identity. S&P Global continues to develop its data and insights capabilities to meet the ever-changing needs of the global market. In a dynamic environment, S&P Global's transparent and reliable solutions provide confidence in making important decisions. As a global standard, customers around the world rely on the data and insights provided by S&P Global in the context of important financial information [22].

2.1.3 Financial Ratios as Predictor Variables

Ratio analysis is highly significant in helping to understand financial statements, identify trends over time, and evaluate the overall financial health of a business. Lenders and potential investors often rely on ratio analysis to assist them in making borrowing and investment decisions [23]. The purpose of financial ratio analysis is to comprehensively evaluate a company's financial condition and performance by considering operational strategies, investment decisions, and funding structures, integrating various aspects found in financial statements [24]. With the help of ratios, companies can assess whether their financial condition is improving or deteriorating and design more effective strategies. Financial ratios not only help in evaluating past performance and planning for the future, but also facilitate comparisons within and between companies [23].

2.1.3.1 Profitability

Profitability ratios are used to analyse the operational health of a company in achieving profits. Good operational health is achieved when a company successfully gains profits from its core activities [23]. High profit levels can enhance the well-being of stakeholders and motivate potential investors to invest [25]. In this study, the profitability value is measured by calculating three ratios: Return on Assets is used to measure the level of profitability or the effectiveness of a company in generating net income from the use of its total assets [11], Return on Invested Capital is a performance ratio that aims to calculate the percentage return generated by a company from the invested capital [26], and Return on Equity is a measure the rate of return on investment for the company's shareholders by relating Net Income After Tax to equity [27].

In research conducted by Soekarno and Kinanthi [11], it is stated that the profitability ratio (ROA) can be used as a benchmark to assess a company's performance. This study aligns with the research by Harsono and Gandakusuma [25] and Mulu and Lecturer [28], which show that the profitability ratio (ROA) significantly impacts a company's performance, where this ratio can distinguish between healthy and unhealthy companies. However, this research contradicts the study by Anggraini and Mulya [29], which states that profitability does not affect a company's financial distress.

2.1.3.2 Liquidity

Liquidity ratios are tools to measure a company's ability to meet its short-term payment obligations. Liquidity ratios indicate whether a company can survive in the long term because companies that struggle to pay short-term obligations have a higher risk of bankruptcy [23]. In this study, liquidity is measured using three ratios: Current Ratio is ratio reflects the company's ability to meet its short-term obligations by comparing total current assets to total current liabilities [24], Working Capital to Total Assets is measure a company's ability to meet its financial obligations and acquire assets that can serve as sources of the company's revenue [30], and CFO to Current Liabilities, this financial metric reveals the amount of operating cash flow generated by the company for each dollar of current liabilities it has.

In their research, Mulu & Lecturer [28] found that liquidity has a positive and significant impact on a company's financial health. This research is also supported by Anggraini & Mulya [29], who stated that liquidity positively affects a company's financial performance. In contrast, research conducted by Dwiantari et al. [31] and Harsono & Gandakusuma [25] explains that liquidity negatively impacts a company's financial performance. However, research by Isayas [32] and Rachman et al. [24] indicates that liquidity does not affect a company's financial performance.

2.1.3.3 Solvency

Solvency or leverage ratios are measures used to evaluate a company's ability to pay long-term debt and associated interest. In the context of solvency, this reflects the company's capacity to meet its financial obligations on time [33]. In this study, solvency is calculated using three ratios: Total Debt to Total Assets this ratio is used to determine the extent to which a company's assets can be financed by liabilities or the extent to which debt affects asset management [34], Total Debt to Total Equity is a metric used to determine the proportion of debt to equity. The lower the DER value, the better the company's ability to repay its long-term debt [35], and CFO to Total Liabilities, this ratio falls under the category of coverage ratios, which are used to calculate the time required for a company to pay off its total debt if all its operating cash flow is allocated for debt repayment [36].

In research conducted by Isayas [32] and Dwiantari et al. [31], it is stated that solvency has a positive influence on the financial difficulties faced by companies, while according to Mulu & Lecturer [28], solvency has a negative impact on a company's financial difficulties. However, according to Rachman et al. [24], solvency does not affect a company's financial performance.

2.1.3.4 Growth Ability

Company growth can be calculated through Asset Growth, revenue growth, and sales growth. Companies with high growth rates tend to attract investor interest because strong growth indicates greater potential profits in the future. Additionally, rapidly growing companies are often considered to have effective management and successful business strategies, which increase investor confidence in the company's stability and long-term prospects [11].

Research conducted by Luh et al. [37] states that company growth (sales growth) has a negative and significant impact on a company's financial difficulties. This research is consistent with the study by Diah & Putri [38], which states that company growth negatively affects a company's financial difficulties. Soekarno & Kinanthi [11] in their research also explain the growth ability of a company as a predictor factor to examine company performance.

2.1.3.5 Cash Generating Ability

According to Kamaluddin et al. [39], cash is considered the most liquid asset, making cash flow a more accurate indicator than the balance sheet in reflecting a company's liquidity position. In the context of theoretical foundations, to evaluate a company's ability to meet its current obligations using cash flow from operating activities, the Operating Cash Flow Ratio (OCFR) can be used. Ratios developed from cash flow statements should complement traditional accrual-based ratios (derived from the balance sheet and income statement) to provide additional information about an entity's financial strengths and weaknesses. These ratios have proven potential in predicting financial failure. The significance of these ratios in predicting company failure lies in their ability to provide insights into the company's capacity to generate cash relative to various financial metrics [40].

Research conducted by Soekarno & Kinanthi [11] found that cash generating ability (CFO to Net Sales) influences company performance. This research is in line with studies conducted by Kamaluddin et al. [39] and Almamy et al. [40], which state that cash generating ability affects company performance. However, according to Diah & Putri [38], operating cash flow negatively affects a company's financial difficulties. On the other hand, research by Tinggi, Trisakti, and Kyai [41] states that operating cash flow does not affect a company's financial difficulties. In this study, cash generating ability is measured in three ways: CFO to Net Sales, CFO to Net Income, and CFO to Cash Flow from Investing.

3.1.4 Discriminant Analysis

The discriminant model is a simple and effective diagnostic tool. Its main advantage is simplicity of interpretation [42]. Discriminant analysis is a statistical approach used to group or classify observations or cases into one of two or more groups based on the characteristics of the observation or case [43]. In the discriminant function analysis process, the explanatory or independent variables must follow a multivariate normal distribution with a similar covariance matrix for each condition of the dependent variable. This makes this technique very robust against assumption violations [11]. This process involves calculating the discrimination coefficient and selecting appropriate weights to effectively separate the values of each group, thereby allowing clear distinctions between groups to be identified [44]. The discriminant function model is presented as follows:

$$\textbf{Z-score} = a + W1\ X1k + W2\ X2k + \ldots + Wn\ Xnk$$

where:

Z-score = Discriminant Z score of discriminant function j for object k
α = Intercept
Wi = Discriminant weight for independent variable i
Xik = Independent variable i for object k

2. 2 Conceptual Framework

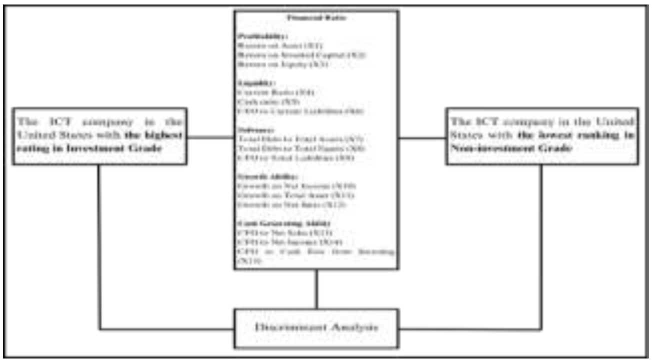

Figure 1: Conceptual Framework

In this research, the designed framework aims to evaluate the differences in financial performance between information and communication technology (ICT) companies in the United States that receive the highest credit ratings in the Investment Grade category and those that receive the lowest ratings in the Non-Investment Grade category. The focus of this analysis is on the evaluation of company performance with financial ratios as predictive variables, grouped into five main categories: Profitability, Liquidity, Solvency, Growth Potential, and Cash Generating Ability. By discriminant analysis, this thesis seeks to identify the most crucial financial ratios in distinguishing between companies with high Investment Grade ratings and those in the low Non-Investment Grade category, providing deeper insights into the financial ratios that influence credit ratings in the ICT industry.

Based on business issues, theories, and literature reviews, researchers formulate the following hypotheses:

H1: There are significant differences in performance between Information and Communication Technology (ICT) companies listed on the U.S. stock exchange with the highest ratings in the Investment Grade compared to those with the lowest ratings in the Non-Investment Group.

H2: Discriminant Function Analysis can be applied to identify performance differences between Information and Communication Technology (ICT) companies listed on the U.S. stock exchange.

H3: There are key factors that distinguish Information and Communication Technology (ICT) companies with the highest ratings in the Investment Grade from those with the lowest ratings in the Non-Investment Group on the U.S. stock exchange.

III. RESEARCH METHOD

3.1 Research Design

The research plan will include several steps for analyzing and producing outcomes. To make the research design in this study easier to read and understand, it will be presented as a flow diagram. This project will have four research stages, which will be carried out in a continuous and serial manner. There are four stages to research: research title, study design, data collection and analysis, and conclusion.

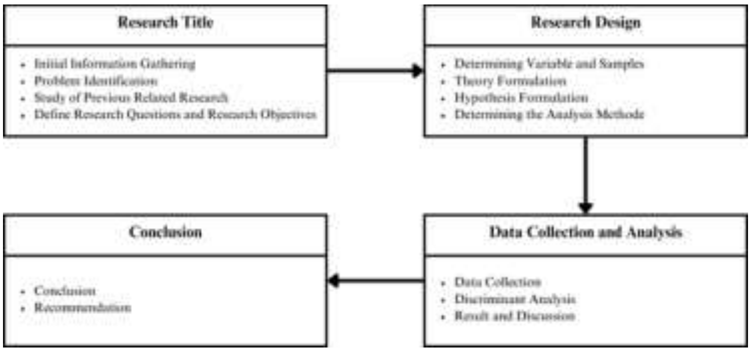

Figure 2: Research Design

3.2 Samples

The sampling technique used in this research is purposive sampling, which is the selection of samples based on the belief that the sample can provide the desired information. The sample selection is done through the Yahoo Finance - Equity Screener feature to find companies that meet the following criteria:

1. Companies listed on the U.S. stock exchange;
2. Companies in the Technology, Communication Services, and Internet Retail sectors (included in the Consumer Cyclical sector);

3. Companies with a market capitalization of more than $2 billion. Companies with a market capitalization above $2 billion are considered mature (Soekarno & Kinanthi, 2020). Mid-cap companies generally have a market capitalization between $2 billion and $10 billion. These mid-cap companies operate in industries expected to experience rapid growth (Fernando, 2024). Therefore, the author chooses a market capitalization above $2 billion as they are considered mature and capable of competing with large companies in attracting investor interest in the capital market;
4. Companies that did not experience losses in the research years, such as 2021 - 2023;
5. Furthermore, the author only selects companies that have received credit ratings from the S&P rating agency.

Based on the above criteria, there are 212 companies listed on the U.S. stock exchange in the selected sectors and industries, with a market capitalization above $2 billion and headquarters in the United States. Finally, 50 companies are selected as samples, with 25 companies from each group, chosen based on the highest ratings in Investment Grade and the lowest ratings in Non-Investment Grade to obtain significant results.

3.2 Variable

According to the literature review, the following financial ratios were chosen as predictor variables for the discriminant function analysis in this research (see Table 1):

Table 1: Research Variables

Name	Symbol	Measurement
ICT company groups in the United States	Y	ICT companies in the Americas with the highest Investment Grade rating receive a score of 1, while those with the lowest Non-investment Grade rating receive a score of 0.
Profitability:		
Return on Asset	X1	net income / total assets
Return on Invested Capital	X2	net income / (total assets – current liability)
Return on Equity	X3	net income / total equity
Liquidity:		
Current Ratio	X4	current assets / current liabilities
Cash Ratio	X5	(cash and cash equivalent + short-term investment or marketable securities) / current liabilities
CFO to Current Liabilities	X6	cash flow from operation / current liabilities
Solvency:		
Total Debt to Total Assets	X7	total debt / total assets
Total Debt to Total Equity	X8	total debt / total equity
CFO to Total Liabilities	X9	cash flow from operation / total liabilities
Growth Ability:		
Growth on Net Income	X10	(net incomet - net income0) / net income0
Growth on Total Asset	X11	(total assetst - total assets0) / total assets0
Growth on Net Sales	X12	(net salest - net sales0) / net sales0
Cash Generating Ability:		
CFO to Net Sales	X13	cash flow from operation / net sales
CFO to Net Income	X14	cash flow from operation / net income
CFO to Cash flow from Investing	X15	cashflow from operation / cashflow from investing

IV. RESULTS AND DISCUSSION

4.1 Classical Assumption test

4.1.1 Multi-Collinearity Test

In the multicollinearity test, the correlation between each of the independent variables is analyzed. This step is primarily to ensure that the predictor variables used in the study meet the assumption of independence or the absence of multicollinearity. Independent variables that show high correlation with each other will be excluded from the model to avoid bias in the research. In this study, a correlation value greater than 0.8 is considered to indicate high multicollinearity and will be excluded in the next step of discriminant function analysis. The following are the results of the correlation among independent variables using the Pearson product moment correlation (Table 2).

Table 2: Multicolliniearity Test Result

Correlations

		X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15
X1		1	.979	.055	.280	.424	.381	.029	-.050	.540	.183	.000	.215	.339	-.148	-.059
X2		.979	1	.088	.181	.343	.294	.089	-.014	.500	.141	-.026	.202	.330	-.144	-.045
X3		.055	.088	1	-.072	-.100	-.126	-.033	.904	.006	.037	.016	.040	-.026	-.008	.052
X4		.280	.181	-.072	1	.816	.550	-.282	-.120	.297	-.002	.052	.110	.121	-.010	-.008
X5		.424	.343	-.100	.816	1	.412	-.380	-.180	.426	-.045	.009	.188	.115	-.056	.045
X6		.381	.294	-.126	.550	.412	1	-.118	-.173	.570	-.070	-.063	.088	.648	-.026	-.134
X7		.029	.089	-.033	-.282	-.380	-.118	1	.025	-.461	.022	-.125	-.151	-.041	-.036	-.249
X8		-.050	-.014	.904	-.120	-.180	-.173	.025	1	-.054	.000	.001	.030	-.080	-.004	.055
X9		.540	.500	.006	.297	.426	.570	-.461	-.054	1	-.096	-.048	.176	.540	-.081	-.027
X10		.183	.141	.037	-.002	-.045	-.070	.022	.000	-.096	1	.270	.170	-.154	-.020	.024
X11		.000	-.026	.016	.052	.009	-.063	-.125	.001	-.048	.270	1	.473	-.031	-.039	.081
X12		.215	.202	.040	.110	.188	.088	-.151	.030	.176	.170	.473	1	.168	-.010	.058
X13		.339	.330	-.026	.121	.115	.648	-.041	-.080	.540	-.154	-.031	.168	1	-.079	-.086
X14		-.148	-.144	-.008	-.010	-.056	-.026	-.036	-.004	-.081	-.020	-.039	-.010	-.079	1	.010
X15		-.059	-.045	.052	-.008	.045	-.134	-.249	.055	-.027	.024	.081	.058	-.086	.010	1

Based on the results of the multicollinearity test (Table 2), there are 6 variables that show multicollinearity values above 0.8, namely X1 (Return on Asset), X2 (Return on Invested Capital), X3 (Return on Equity), X4 (Current Ratio), X5 (Working Capital to Total Assets), and X8 (Total Debt to Total Equity). The other variables do not show multicollinearity issues and can proceed to the next analysis stage. Initially, the study consisted of 15 variables, but after the multicollinearity test, it was reduced to 9 variables. Thus, the initial and final variables are as follows:

Table 3: List of Initial and Final Variables

No	Variable Awal		Variable Akhir	
1	X1	Return on Asset	X6	CFO to Current Liabilities

2	X2	Return on Invested Capital	X7	Total Debt to Total Assets
3	X3	Return on Equity	X9	CFO to Total Liabilities
4	X4	Current Ratio	X10	Growth on Net Income
5	X5	Working Capital to Total Assets	X11	Growth on Total Asset
6	X6	CFO to Current Liabilities	X12	Growth on Net Sales
7	X7	Total Debt to Total Assets	X13	CFO to Net Sales
8	X8	Total Debt to Total Equity	X14	CFO to Net Income
9	X9	CFO to Total Liabilities	X15	CFO to Cash flow from Investing
10	X10	Growth on Net Income		
11	X11	Growth on Total Asset		
12	X12	Growth on Net Sales		
13	X13	CFO to Net Sales		
14	X14	CFO to Net Income		
15	X15	CFO to Cash flow from Investing		

4.1.2 Uji Box's M Test

After performing the multicollinearity test, the Box's M test is conducted. The Box's M test is used to ensure that all covariance matrices among variable groups do not differ multivariately. The results of the Box's M test (Table 4) show an F-value of 5.333 with a significance level of 0.000, which is less than 0.05. This indicates that the covariance matrices among the groups are different. The Box's M test is very sensitive to any minor deviations that violate homogeneity. Nevertheless, discriminant function analysis remains robust even if the homogeneity of variances assumption is not met, provided that the data does not contain outliers (Ghozali, 2018).

Tabel 4: Box's M Test Result

Test Results		
Box's M		32.716
F	Approx.	5.333
	df1	6
	df2	158700.679
	Sig.	.000
Tests null hypothesis of equal population covariance matrices.		

4.2 Interpretation of Model Accuracy and Significance Difference Test

4.2.1 Test of Equality of Group Means

The subsequent step involves identifying the significant factors that differentiate the two groups. The **Test of** Equality of Group Means table displays the Wilk's Lambda values, which range from 0 to 1. A Wilk's Lambda value closer to 0 indicates that the characteristic significantly distinguishes between the two group variations, and vice versa.

Table 5: Test of equality of group means

Tests of Equality of Group Means					
	Wilks' Lambda	F	df1	df2	Sig.
X6	.994	.872	1	148	.352
X7	.898	16.741	1	148	.000
X9	.896	17.101	1	148	.000
X10	.989	1.634	1	148	.203
X11	.997	.390	1	148	.533
X12	.972	4.265	1	148	.041
X13	.874	21.350	1	148	.000
X14	.992	1.255	1	148	.264

X15	.973	4.080	1	148	.045

From the results, it can be seen that the Wilks' Lambda values for these variables are close to 1, making it difficult to identify significant differences. Therefore, another method to identify significant variables that distinguish between the two groups is using the F Test. If the significance value (Sig) is above the 5% level, it indicates no difference between the groups; if the significance value is within the 5% level, it indicates a difference between the groups. Based on the calculations in Table 5, it is observed that out of 9 variables, 5 variables significantly differentiate between high investment grade and low in non-investment grade companies. The significant variables are X7 (Total Debt to Total Assets), X9 (CFO to Total Liabilities), X12 (Growth in Net Sales), X13 (CFO to Net Sales), and X15 (CFO to Cash Flow from Investing), while the other variables do not significantly differentiate the two groups.

4.2.2 Selection The Most Influential Ratios Prediction Analysis

To determine which variables are most efficient in differentiating between companies categorized as high investment grade and low investment grade, the stepwise method is utilized. Then it can be seen from the test results as follows.

Table 6: Stepwise Test Result

Variables Entered/Removed[a,b,c,d]							
Step	Entered	Min. D Squared					
		Statistic	Between Groups	Exact F			
				Statistic	df1	df2	Sig.
1	X13	.569	Higest and Lowest	21.350	1	148.000	0.000
2	X7	1.106	Higest and Lowest	20.590	2	147.000	0.000
3	X6	1.508	Higest and Lowest	18.595	3	146.000	0.000
At each step, the variable that maximizes the Mahalanobis distance between the two closest groups is entered.							
a. Maximum number of steps is 18.							
b. Maximum significance of F to enter is .05.							
c. Minimum significance of F to remove is .10.							
d. F level, tolerance, or VIN insufficient for further computation.							

Because this research aims to identify the most dominant variables in distinguishing financial conditions between high investment grade and low non-investment grade companies, the stepwise method is employed by maximizing the Mahalanobis Distance (Table 6) to determine the variables with the greatest discriminative power. The stepwise procedure begins by including the variables that maximize the Mahalanobis Distance between the two groups of companies. In this context, a minimum significance value of 0.05 is used as the criterion for variable inclusion, and the Mahalanobis Distance is used to select the variables with the strongest discriminative power. Based on the test results in the Min D squared table, it is evident that through the stepwise process, only three variables have a significance value below 0.05: X13 (CFO to Net Sales), X7 (Total Debt to Total Assets), and X6 (CFO to Current Liabilities).

4.2.3 Test of Eigenvalues

Table 7: Summary of canonical discriminant function

Eigenvalues				
Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.382[a]	100.0	100.0	.526
a. First 1 canonical discriminant functions were used in the analysis.				

The results of the Eigenvalues test (Table 7) indicate that the canonical correlation value is 0.526, or 52.6%. This means that the three variables contribute 52.6% to the variable y. This finding reinforces the earlier statement from the stepwise test that the three variables, X13 (CFO to Net Sales), X7 (Total Debt to Total

Assets), and X6 (CFO to Current Liabilities), significantly influence the performance of ICT companies. These three variables are considered the most influential financial ratios in distinguishing between high investment grade ICT companies and low investment grade ICT companies.

4.2.4 Test of Wilk's Lambda

Table 8: Wilk's Lamba Test Result

Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.724	47.407	3	.000

The Wilk's Lambda model is used to measure the extent to which independent variables can distinguish the dependent variable, which in this study refers to the performance of joint venture insurance companies. This model is also part of Discriminant Analysis to ensure its adequacy for use in this research. The table above (Table 8) shows the final value of Wilk's Lambda and a Chi-square value of 47.407 with a significance level of 0.000, indicating a high level of significance and a clear difference between the two groups studied. In this context, group 1 represents companies with an Investment Grade rating, while group 0 represents companies with a Non-Investment Grade rating. This result indicates that H0 is rejected and H1 is accepted, meaning there is a significant difference in the performance of ICT companies between those with Investment Grade and Non-Investment Grade ratings, as explained by the predictor variables.

4.3 Forming the Discriminant Function

4.3.1 Canonical Discriminant Function Coefficient

Table 9: Canonical Discriminant Function Coefficient

Canonical Discriminant Function Coefficients

	Function
	1
X6	1.064
X7	2.816
X13	-10.556
(Constant)	.003

Unstandardized coefficients

The Canonical Discriminant Function Coefficients are unstandardized values used to construct the actual prediction equation, which can classify new cases (see Table 9). Similar to regression analysis, the model in discriminant analysis consists of a constant and variables, each with coefficients that determine the score (Z score). Based on the table of Canonical Discriminant Function Coefficients, the following equation can be derived:

$$Z=0.003+1.064X6+2.816X7-10.556X13$$

From this equation, it can be seen that the variables CFO to Current Liabilities and Total Debt to Total Assets have positive signs, indicating that if the values of these ratios are high, the company's performance will improve. Conversely, the variable CFO to Net Sales has a negative sign, suggesting that if the value of this ratio is high, the company's performance will decline.

4.3.2 Calculate the Optimal Cutting Score

Table 10: Function of Group Centroid

Functions at Group Centroids	
Investment Grade	Function
	1
Highest	-.614
Lowest	.614
Unstandardized canonical discriminant functions evaluated at group means	

Functions at Group Centroid is utilized to set the cutoff point for categorizing companies with high investment grade and non-investment grade. The analysis results from functions at group centroid (Table 10) indicate a cutoff value of 0.614. This implies that if the value is less than 0.614, the company is classified as having high performance (highest), and if the value is greater than 0.614, the company is classified as having low performance (lowest).

4.3.4 Classification Accuracy test

The table (Table 11) above illustrates the predictive accuracy of the discriminant function. The accuracy rate ranges from 0-100%, with values closer to 100% indicating higher accuracy. The classification results indicate that the prediction accuracy for high investment grade companies is 73.3%, meaning there is a 26.7% prediction error for this category. In contrast, the prediction accuracy for non-investment grade companies is 69.3%, indicating a 30.7% prediction error for this category. Overall, the data in the table reveals that the discriminant analysis can predict the performance of companies with an overall accuracy of 71.3% during the research period of 2021-2023, encompassing both high investment grade companies and non-investment grade companies.

Table 11: Classification Result

		Kinerja	Predicted Group Membership		Total
			Higest	Lowest	
Original	Count	Higest	55	20	75
		Lowest	23	52	75
	%	Higest	73.3	26.7	100.0
		Lowest	30.7	69.3	100.0
a. 71.3% of original grouped cases correctly classified.					

V. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The results of this study show that the null hypothesis (H0) is rejected, and the alternative hypothesis (H1) is accepted. This means that the financial ratios used as variables in the discriminant function analysis can differentiate the performance of ICT companies between those in the Investment Grade group and the Non-Investment Grade group based on credit ratings.

Furthermore, this model proves that financial ratios are still effective in assessing the performance of ICT companies in the current digital era. Thus, the second hypothesis (H2) is also accepted, indicating that discriminant function analysis can be used to identify performance differences between Information and Communication Technology (ICT) companies listed on the US stock exchange. According to the study results, this model has a predictive accuracy of 71.3% during the study period of 2021-2023. Therefore, this predictive model is highly recommended because it can predict the future performance of ICT companies well.

Of the 15 financial ratios selected as predictor variables, only three consistently and effectively differentiate between ICT companies in the Investment Grade and Non-Investment Grade categories. These ratios are CFO to Net Sales (X13), Total Debt to Total Assets (X7), and CFO to Current Liabilities (X6). All these ratios must be used together in the discriminant function model resulting from this study. This also shows that the third hypothesis (H3) is accepted, meaning that there are key factors that distinguish Information and Communication Technology (ICT) companies with the highest ratings in the Investment Grade from those with the lowest ratings in the Non-Investment Grade group in the US stock market. Therefore, one of the main objectives of using Discriminant Analysis in this study to develop a Discriminant Function that can be used to predict the performance of ICT companies in the United States is fulfilled. The Discriminant Function resulting from this study is: $Z=0.003+1.064X6+2.816X7-10.556X13$

However, the predictive model resulting from this analysis has several limitations and weaknesses. First, the study's temporal scope is limited to the period from 2021 to 2023, potentially missing long-term trends and structural changes. Second, the study focuses solely on financial variables, neglecting non-financial and external factors such as investor sentiment, business strategies, and innovation developments, which can also significantly impact company performance. Third, the study relies only on S&P Global credit ratings as the benchmark for assessing company performance due to the lack of a specific standard for evaluating the financial performance of ICT companies. This limitation affects the model's ability to generalize to all ICT companies, as the sample is restricted to those with existing ratings. Additionally, the sample size is limited to 25 ICT companies in the Investment Grade group and 25 in the Non-Investment Grade group, which may constrain the model's representativeness. A larger and more diverse sample could provide more comprehensive insights.

For future research, extending the study period and including more company data could provide a better understanding of trends and changes within the industry. Incorporating non-financial and external company variables would offer a broader view of the factors influencing company performance. Additionally, using other credit ratings such as those from PT Fitch Ratings, Moody's Investor Service, and other relevant factors might better reflect a company's performance. Finally, expanding the sample to include more ICT companies in the United States would enhance the model's representativeness. By addressing these limitations and continuing research in this direction, it is anticipated that deeper and more comprehensive insights into the factors influencing the performance of ICT companies in the United States will be obtained.

5.2 Recommendation

For Investor

The researcher recommends this model to investors as it serves as a quantitative tool that can complement qualitative analyses, such as economic aspects or future business prospects of ICT. With its ability to distinguish between high-performing and low-performing companies, this model allows investors to allocate their resources more efficiently, potentially maximizing profits and minimizing risks. The findings from this research will help investors identify promising investment opportunities in the ICT sector based on financial performance indicators.

For Internal Management of The Company

The researcher also recommends this model to managers and executives of ICT companies who are stakeholders in this study. By utilizing insights from the discriminant function analysis, this model can be used as an internal control tool to monitor the company's financial performance, allowing for preventive measures when there are indications of declining performance. Additionally, company leaders can assess their company's performance relative to industry competitors, identify areas for improvement, and make data-driven strategic decisions to enhance competitiveness and profitability. This research provides managers with valuable data-based insights to drive organizational growth and sustainability.

For Academic and Future Research

The researcher recommends this study as a reference for further research, particularly regarding the relationship between financial information and the performance of ICT companies. Future researchers can also use this study as a basis for conducting additional research that compares different variables affecting company performance with various rating systems, thus enriching the overall understanding. Besides being useful for the general public, this study also demonstrates that financial information, previously considered less relevant to ICT businesses in the digital era, can actually be instrumental in assessing or serving as a benchmark for the future performance of ICT companies based on financial ratios.

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