WORKING CAPITAL POLICY CLUSTERING TECHNIQUE: A CASE STUDY OF LISTED COMPANIES IN THE INDUSTRIAL SECTOR, MAI THAILAND

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Abstract

Working capital policy (WCP) has an impact on liquidity and profitability management. An aggressive WCP allows businesses to generate profits from short-term capital sources but poses risks in timely short-term debt repayment. Determination of WCP involves various factors. Previous studies found that the risk level of the working capital policy is solely determined by the financial ratio, overlooking other contributing factors. This research aimed to enhance the coverage of risk dimensions in setting the risk level of WCP by introducing a clustering technique to determine the WCP risk level. The study population consisted of 213 companies listed on the Market for Alternative Investment (MAI). A specific sampling method was employed, focusing on companies within the industrial sector registered on the MAI. This study utilized panel data by gathering financial ratio data from the STATA database and executive position data (CEO, President) through the annual report Form 56-2 from the SEC database. Data collection spanned 15 consecutive years, from 2008 to 2022, divided into two periods: the COVID-19 pandemic outbreak and the non-pandemic period, which resulted in a total of 432 observations. The hierarchical clustering analysis technique was utilized, followed by K-means cluster analysis and one-way ANOVA robustness checks. The results revealed that the working capital investment policy (WCIP) could be categorized into three sub-groups: risky, moderate, and conservative. The working capital financing policy (WCFP) could be classified into two sub-groups: risky and conservative. K-means clustering analysis for risk levels identified two groups: a risky and a conservative WCP. One-way ANOVA analysis for group differentiation indicated three sub-groups for both policies.

Keywords: Hierarchical, K-means Clustering, Working Capital Policy, Aggressiveness

Introduction

Managing working capital is a pivotal aspect of business financial management, involving the formulation of working capital policies and assessing their efficiency (Banchuenvijit, 2017; Pestonji & Wichitsatian, 2019) Working capital policies determine the amount and sourcing of working capital, focusing on major components such as cash, accounts receivable, and inventory (Brigham & Houston, 1998). Efficiency in working capital management ensures the optimal use of current assets and short-term debts to maintain smooth business operations (Intara & Wanganusorn, 2022). Investment in working capital involves determining the quantity of working capital relative to sales. Businesses with low reserves can invest surplus capital in non-current assets, generating additional income and increasing overall revenue (Kasiran et al., 2016). This reinvestment in income-generating assets enhances profitability and signals improved operational performance to investors, which can increase the market price of common stocks and enterprise value (Berk et al., 2009; Myers & Majluf, 1984) Conversely, a high reserve policy ensures adequate product supply, preventing missed profit opportunities and minimizing the risk of stockouts (Baños-Caballero et al., 2020; Mansoori & Muhammad, 2012). Technological advancements can negatively impact businesses by making products obsolete and introducing lower-priced substitutes (Intara & Wanganusorn, 2022). Failure to meet sales targets can result in financial losses due to significant investments in remaining inventory, decreasing enterprise value (Intara & Wanganusorn, 2022; Kasiran et al., 2016; Song et al., 2012). WCP also plays a crucial role. Businesses that obtain funds from short-term sources for permanent working capital (Aggressive Investment Policy) can save financial costs, improving operational performance and enterprise value (Pestonji & Wichitsatian, 2019). This aligns with the pecking order theory, which suggests prioritizing low-cost funding sources, including internal funds from trade creditors and accrued expenses, to enhance profitability and enterprise value (Myers & Majluf, 1984). Issuing additional shares as a funding strategy may signal financial challenges to investors (Brigham & Daves, 2007).

In Thailand, businesses can raise capital through the stock market, divided into the Stock Exchange of Thailand (SET) and the Market for Alternative Investment (MAI). The MAI facilitates fundraising for SMEs with potential but lacking capital, with 206 SMEs registered, raising over 479,383 million baht (SET, 2023). These SMEs play a vital role in the Thai economy by addressing economic issues and supporting job creation, contributing to direct and indirect investments that propel economic growth. The literature review on factors affecting business value in the MAI reveals challenges such as long-term survival, data inconsistency, bankruptcy trends, and failures in working capital management (Banchuenvijit, 2017; Chancharat & Chancharat, 2019; Intara & Wanganusorn, 2022; Phromsuwansiri et al., 2022). These challenges highlight the importance of effective working capital management in ensuring the survival of companies in the MAI market. Previous studies on the relationship between working capital management policies and business performance categorize risk levels into Aggressive and Conservative Approaches (Adam et al., 2017; Nazir & Afza, 2009; Sudiyatno & Elen Puspitasari, 2017), or into Aggressive, Moderate, and Conservative Approaches (Pestonji & Donkwa, 2018; Vishnani & Shah, 2007) While some studies find a significant relationship between working capital policies and business performance, others do not, suggesting the need for further research.

To provide a comprehensive understanding, this study investigates factors influencing the determination of risk levels in working capital management policies using a Clustering Technique to classify different risk levels.

Research Objectives

To investigate the factors influencing the determination of risk levels in working capital management policies using a Clustering Technique

Literature Review

The Clustering Technique

The Clustering Technique is a statistical method used to group similar data based on their characteristics. It categorizes data by placing those with the highest similarity into the same group, while different data are assigned to separate groups (Gupta et al., 2011). This technique has been applied in various research areas and industries, such as: 1. In the medical field: Grouping patients based on urgency (McLachlan, 1992). 2. In the Biology field: Analyzing Genome-Wide Association Studies (GWAS) to identify data groups related to disease or cancer strains (Sharma et al., 2017). 3. In the Business Management field: Arranging product positions to meet customer needs and segmenting markets (Punj & Stewart, 1983; Saunders, 1980). The main types of clustering techniques include: 1. Partitioning Methods: This approach divides data into groups based on the most similar characteristics, creating a predefined number of K groups (where K is the desired number of groups) The user needs to specify the number of groups or clusters they want to create (denoted as 'k'). In the K-Means technique, the algorithm operates through multiple iterations. In each iteration, cases are assigned to a group based on minimizing the distance from the group's centroid. The centroid is then recalculated, and this process is repeated until the centroid values no longer change or until a predefined number of iterations is reached. This technique requires quantitative variables, specifically those on the interval or ratio scale, and cannot be applied to categorical or binary data, in contrast to the Hierarchical technique. 2. Hierarchical Methods: This method divides groups based on similar characteristics at each level until the desired group is obtained. The choice of clustering technique depends on the nature of the data and the objectives of the analysis. Therefore, literature review and statistical experiments may be used to select the most suitable technique for grouping highly diverse data. The Hierarchical Cluster Technique categorizes cases without the need to determine a specific number of clusters in advance or to know which group each case belongs to. This method is suitable for datasets with a relatively small number of cases and is compatible with nominal scale or binary data. The technique creates a tree-like structure, or dendrogram, representing the relationships between cases. At each step, the algorithm combines the closest cases or clusters until all cases are grouped. This method is flexible and can be applied to various types of data, including those with nominal scale or binary measurements.

Research Methodology

This research adopts a quantitative approach with secondary data to study the aggressiveness of working capital policies. The relevant factors associated with the determination of these policies are used to categorize companies registered in the Industrial sector in MAI into subgroups based on their risk levels. The comparison of grouping outcomes is performed through K-mean clustering and One-Way ANOVA.

Population and Sample Group Selection:

- Population: The population comprises companies registered in the MAI market, totaling 213 companies across eight major industry groups and 30 subcategories.

- Sample Group Selection: A targeted sampling method is employed, selecting companies registered in the Industrial Industry with complete data.

Data Collection and Analysis:

- Data Collection: This research utilizes panel data, gathering financial ratio data from the STATA database and executive position data (CEO, President) through the annual Form 56-2 from the SEC database. Data collection spans 15 consecutive years, from 2008 to 2022, divided into two periods: the COVID-19 pandemic outbreak period and the non-pandemic period, resulting in a total of 432 observations.

- Data Analysis:

1. Cluster Analysis:

Hierarchical Cluster Analysis groups cases or variables based on these conditions: 1). Number of Cases: Suitable for fewer than 200 cases. For more, K-Means Cluster is recommended. 2). No Prior Knowledge: The number of groups does not need to be known beforehand. 3). Initial Group Membership: It is unnecessary to know which variables or cases belong to specific groups initially (Wanichbancha, 2009). The process starts with n subgroups, merging the closest or most similar items iteratively until one group remains. The Linkage method is commonly used in Agglomerative Hierarchical Cluster Analysis, with three main types: 1). Single Linkage: Measures the distance between the closest elements. 2). Complete Linkage: Measures the distance between the farthest elements. 3). Average Linkage: Measures the average distance between all elements. This creates a dendrogram, showing relationships between subgroups. The choice of linkage method depends on data characteristics and clustering goals. Ward's Method, This study uses Ward's Method (Gupta et al., 2011), which minimizes the sum of squared differences within clusters. The distance between clusters C_i and C_j is given by:

$$d(C_i, C_j) = \sqrt{\frac{|C_i| \cdot |C_j|}{|C_i| + |C_j|}}\ \mathrm{dist}(m_i, m_j)$$

Where m_i and m_j are the centroids of cluster C_i and C_j respectively in these formulas: C_i and C_j are clustered being compared. $|C_i|$ and $|C_j|$ represents the number of elements in clusters C_i and C_j respectively. Dist (m_i, m_j) is the distance between the centroids of C_i and C_j clusters. The linkage method choice depends on the data's characteristics and the clustering goal. The hierarchical clustering process is often visualized using a dendrogram, where the y-axis represents the distance at which clusters are merged or split to group companies based on similar financial and executive characteristics.

2. Robustness check; Employ K-mean and Mean Difference Analysis which applies One-Way ANOVA to test the relationship between subgroups and the outcomes of groupings then Comparative Analysis of Grouping Results.

Table 1: Variables Used in Analysis:

Variables summary and measurement	Desired Value to be high Aggressiveness
Current Assets to Sales Ratio Measures the level of investment in working capital. A higher ratio indicates lower risk. It is calculated as Current Assets/Sales.	-Low
Inventory Turnover Rate Indicates the speed of selling goods. A higher turnover suggests efficient sales, while a low one may indicate higher risk. Calculated as Cost of Goods Sold/Average Inventory.	-High
Accounts Receivable Turnover Rate Reflects investment in trade receivables. A high turnover indicates quicker collection, while a low one may signify a lenient credit policy. Calculated as Sales on Credit/Average Trade Receivables.	-High
Current Liabilities to Sales Ratio Measures liquidity. A ratio greater than 1 indicates excess short-term funds for debt payment, suggesting low risk. It is calculated as Current Liabilities/Sales.	-High
Current Assets to Current Liabilities Ratio Reflects business liquidity. A ratio greater than 1 indicates excess working capital, suggesting low risk. It is calculated as Current Assets/Current Liabilities.	-Low
Debt to Non-Current Liabilities Ratio Indicates financial leverage. A high ratio suggests high risk. It is calculated as Long-term Debt/Non-Current Liabilities.	-High
Free Float Reflects stock ownership dispersion, impacting decision-making difficulty. Greater dispersion suggests lower management risk.	-Low

CEO Duality The nominal variable indicates whether the President also holds the CEO position. Duality may suggest higher risk due to consolidated decision-making power.	-High

Results

According to the WCIP clustering result, hierarchical clustering with the ward algorithm, dendrogram, and the Auto Clustering Akaike's Criterion (AIC) tests was utilized to validate clusters, The result revealed that the optimal group based on the dendrogram is categorized WCIP into 3 groups as shown in Figure1. The AIC test indicated that the optimal group of WCIP clustering is 10 group. It is because after the elbow joint, the decrease becomes notably smaller however, it is meaningless for the subgroups more than 3. For this reason, WCIP was categorized into 3 groups which consisted of aggressive WCIP, moderate WCIP, and conservative WCIP. For WCFP clustering result, is quite similar to WCIP but the optimal categorization is only 2 categories including aggressive WCFP and conservative WCFP.

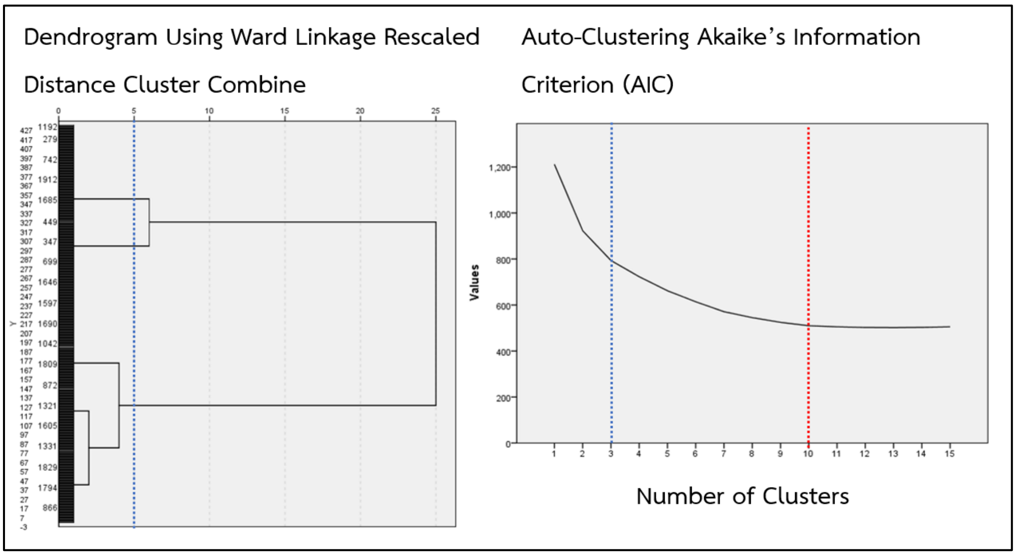

Figure 1: Dendrogram and AIC Test for WCIP

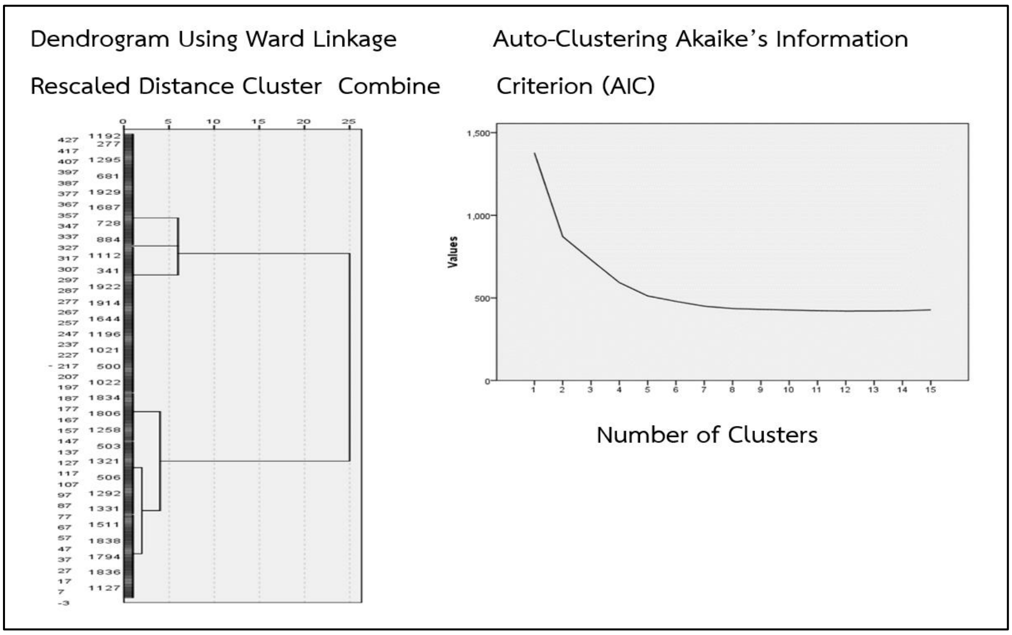

Figure 2: Dendrogram and AIC Test for WCFP

Robustness Test

K-Mean clustering

In this study, K-mean clustering and a One-way ANOVA test were employed to make robustness. As the K-mean clustering part, this study uses a simulation of K (number of group clustering) broken into 2 cases with K=2 and 3, in which K =2 denotes a group of aggressive and conservative WCIP. In contrast, K=3 denotes a group of aggressive, moderate, and conservative WCIP respectively. To assign the definition to each group, this study employed the desired Value coupled with the final cluster center to determine the group characteristic. The result shows that at K = 2 the WCIP iteration is stable in the 4th round and at K=3 the WCIF iteration is stable in the 8th round which indicates that clustering WCIP into 2 groups is more precise. For WCFP, the iteration is stable in the 3rd at K=2 and stable in the 4th at K= 3 which implies that the 2 group is suitable for WCFP. In other words, WCFP should be an aggressive and conservative group. Moreover, this study presents the average mean of each variable for each group clustering which is proxy by the K-mean final cluster center The result found that there are notable differences in the mean between the aggressive group and conservative group e.g. The Free Float (WCIP) within the aggressive group exhibits a mean value of 0.90, indicating a substantial contrast with the conservative group, where the mean value is 32.9. This notable difference in mean values suggests a significant disparity in the level of free float between companies classified as aggressive and those classified as conservative in the WCIP clustering.

One-Way ANOVA Test

ANOVA results demonstrate the variables that significantly contribute to the formation of the clusters. The top factor that affected WCIP clustering was explained by the combination of the mean square of the cluster and the mean square of error shown as F is FRD for K= 2(F =984.03) and for K=3 (F=1618.09). Regarding WCFP, CLTN emerges as the predominant factor, exhibiting the highest F values (F=1332.167 with K=2 and F=1099.65 with K=3), influencing group clustering. In the summary from the ANOVA test, three subgroups for both WCIP and WCFP are preferable.

Discussion

In previous study WCP (WCIP and WCFP) was categorized into three main subgroups consisting of an aggressive policy, moderate policy, and Conservative policy with single criteria utilized e.g. current asset /total asset with a cut-off rate of 0.5 (Raheman et al., 2010), current liability to total asset, short-term debt to the total asset, using One-way ANOVA as clustering criteria (Pestonji & Wichitsatian, 2019). Besides, the study conducted by (Chancharat & Kumpamool, 2020) used the average industry indicator as a base case, for a value that is greater than the mean value is supposed to be an aggressive policy, and below the mean is supposed to be a conservative policy. In this study, the clustering technique was employed with hierarchical clustering and robustness by K-mean and One-way ANOVA test. The results reveal the 3 different outputs (WCP subgroup) by hierarchical clustering, the optimal subgroup for WCIP is 3 (Aggressive, Moderate, and Conservative subgroup) and for WCFP is 2(Aggressive and Conservative): for K-mean clustering, the optimal WCP subgroup is 2: for One-Way ANOVA test the optimal WCP subgroup is 3 (Aggressive, Moderate, and Conservative subgroup) in line with (Pestonji & Wichitsatian, 2019). One factor accounting for variations in clustering output is the inherent variability in the characteristics of variables, stemming from differences in their levels of measurement. Notably, the utilization of nominal scale data is precluded in the K-means clustering method, contributing to disparities in the clustering outcomes.

Body of Knowledge

In addition to the working capital management concept, the working capital policy illustrates the short-term liquidity management guidelines, which represent the degree of business aggressiveness. Prior research has examined the relationship between WCP and FP (Chancharat & Kumpamool, 2020; Pestonji & Wichitsatian, 2019; Raheman et al., 2010). Three distinct relationships were found: the first is positive, indicating that aggressive policies perform better; the second is negative, indicating that conservative policies perform better; and the third, there is no relationship at all. By the concept of clustering WCP with risk-taking characteristics, moderate characteristics, or conservative characteristics prior research has determined this characteristic by using only a single financial ratio to determine risk appetites, such as the current asset /total asset with a cut-off rate of 0.5 (Raheman et al., 2010), current liability to total asset, short-term debt to the total asset and short-term debt to total assets (Pestonji & Wichitsatian, 2019). By the way, The changes in the business environment led to another factor that affected WCP formulation. Based on the Agency theory, as the executives do not own 100% of the shares implies that there is a change of agency problems due to conflicts of interests. Determining a working capital policy is one of the executive's decisions If there is a low level of distribution of shareholding (Free Float) coupled with the action of the president as executive chairman (CEO duality) could lead to an increase in aggressive WCP. To fulfill the dimensions for WCP formulation, this research utilizes several factors expected to affect the determination of WCP e.g. free float, CEO Duality, the ratio of current assets to sales, and another related financial ratio to participate in determining WCP as shown in Figure 3. Aggressive WCP represents the highest risk-taking policy as the Moderate and Conservative WCP refer to the risk-neutral and risk-averse respectively.

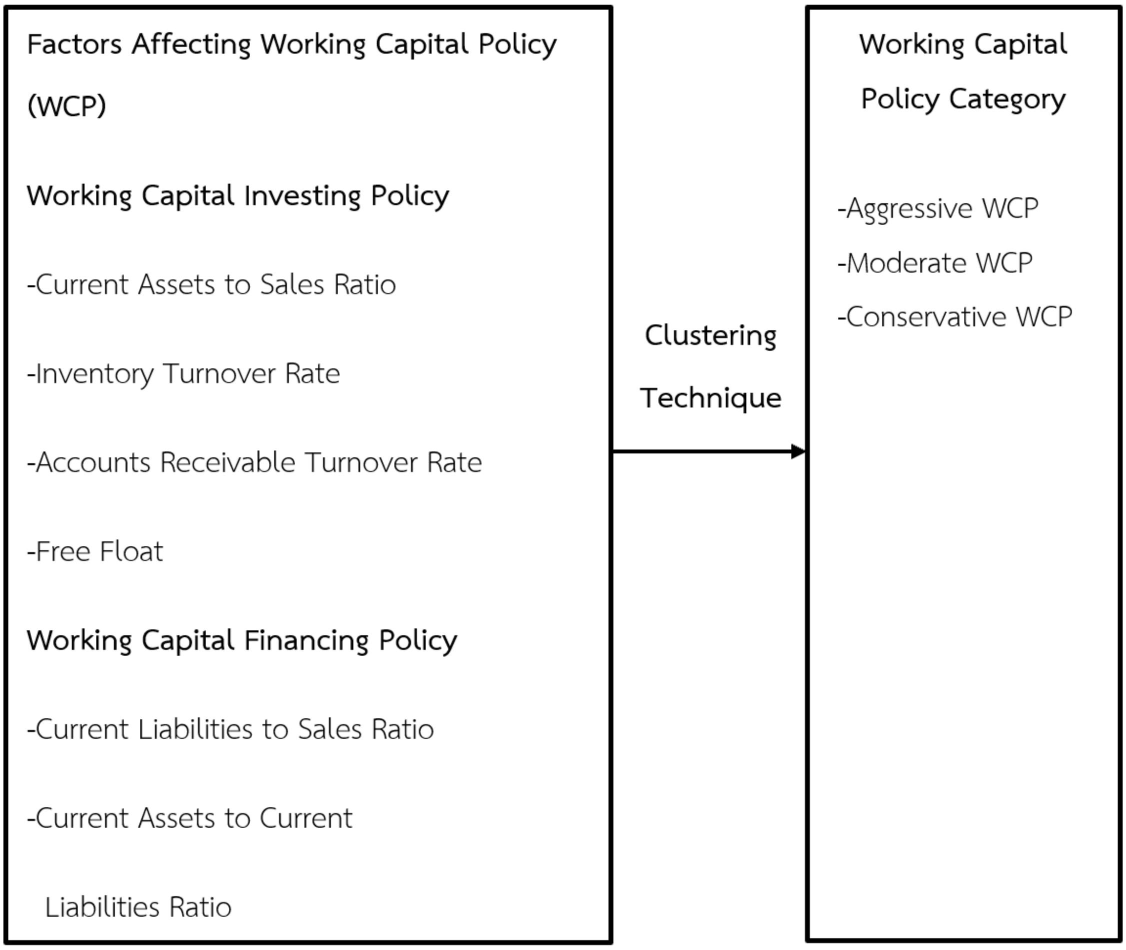

Figure 3: Factor affecting working capital policy

Conclusion

WCM is the crucial factor affecting business performance. WCP is a part of WCM which is specific to policy implementation. It demonstrates the level of aggressiveness which leads to the increase in FP. Beyond the MAI context, WCP is a success key factor because of the restriction in working capital capability e.g. it is hard to access low-cost funding, and it's hard to deal with mass production. To identify the level of aggressiveness, several studies focus on a single ratio to conduct the level of aggressiveness which may result in losing some key factors. The study population consisted of 213 companies listed on MAI. A specific sampling method was employed, focusing on companies within the industrial sector registered on the MAI from 2008 to 2023, totaling 432 observations. This study employed Hierarchical Clustering to identify the level of aggressiveness and make robustness checks by K-means Clustering and One-Way ANOVA. The results revealed that the WCIP could be categorized into three subgroups: risky, moderate, and conservative. The WCFP could be classified into two sub-groups: risky and conservative. K-means clustering analysis for risk levels identified two groups: a risky WCFP and a conservative WCIP. The One-Way ANOVA analysis for group differentiation indicated three sub-groups for both policies.

Suggestions

Applying the Study Findings:

This research has examined the stratification of aggressiveness levels associated with the implementation of working capital policy. Under the classification of companies in the INDUST industry using hierarchical clustering and K-WAY ANOVA techniques to assess the risk levels of working capital policies (WCP) employing various factors thought to influence the formulation of these policies as components in measuring their risk levels. The study found that both hierarchical clustering and K-WAY ANOVA techniques yielded consistent results, allowing for the categorization of companies into three groups based on their risk appetite in employing working capital policies. Those interested in studying the deep relationships of differences or the impacts of employing working capital policies in various forms that affect operational performance can utilize the aforementioned techniques in categorizing companies to better explain the relationships of companies within each group.

Recommendations for Future Research:

According to the limitation of The K-Mean technique, the measurement level of the variable entered must be interval scale and or ratio scale which leads to the loss of some variables whose scale is Nominal or ordinal scale

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