__Review Article__

Textile and Garment Sector Financial Distress and Its Prediction: A Systematic Indonesia Literature Review

ABSTRACT

Aims: The purpose of this study is to examine the conceptualization of financial distress research in the textile and apparel industries, particularly in terms of research scope and methodology. Furthermore, this article attempts to systematically analyze the network formed by these literatures.
Methodology: In this study, a qualitative approach was used through the literature review method, with 41 specific articles about financial distress in the textile and garment sector serving as the research corpus and drawn from the Litmaps database. To interpret and describe the frequency patterns and relationships visualized using RStudio and Gephi devices, text mining, network analysis, and content analysis were used.
Result: This study discovers that a frequently discussed issue is the influence of financial variables, both dependent and independent, on the prediction of financial distress or vice versa, using various quantitative approaches and models of financial distress. This claim is supported by the findings of a systematic analysis, which reveals a positive correlation between global cloud output and network analysis.
Implication/Applications: The corpus aspect of this research is limited, and the research scope is limited to the Indonesian context. Future research with broader literature sources and different types of company sectors is highly anticipated. This literature review can provide a comprehensive framework for researchers and practitioners who are interested in cases of financial distress.
The originality of the study: Furthermore, this is a recent study that conducts a systematic review of the literature on financial distress in Indonesian textile and garment companies.

Keywords: Financial distress, textile and garment sector, literature review, systematic network analysis

1. INTRODUCTION

Methods of assessing the risk of corporate financial distress have long been studied in economic and financial literature. For decades, researchers and practitioners have worked to develop new methods for forecasting financial distress and bankruptcy (1). Until recently, firm pressure prediction techniques relied on a static single-period model to distinguish between stress and non-stress firms. Prior to the development of the quantitative approach, in the 1930s, a qualitative approach was also used to assess the creditworthiness of certain traders. Beaver's Univariate Analysis, published in 1966, is regarded as the first classic in the field of ratio analysis and bankruptcy classification (2). Several other works that have also begun to appear to include Altman's Multivariate Analysis (1968), The Model of Ohlson (1980), The Model of Zmijewski (1984), and The Neural Networks of Etheridge and Sriram (1997).

Currently, financial ratio analysis is a popular managerial tool as well as a tool for determining a company's economic activity (3,4). In a nutshell, this prediction is based on a functional correlation calculation between the financial ratio and a number of dependent variables. This model is commonly used by investment analysts for a variety of purposes, including predicting profitability, predicting a company's failure, assessing potential risks, and assisting in credit rating. In general, the analysis seeks the most useful financial ratios that provide significant information about future events to be used in models for predicting financial distress or bankruptcy (5,6).

Despite the fact that financial difficulties have changed dramatically over the last decade, owing in part to significant changes in financial law and markets, research on financial distress has previously focused on distress costs and financial restructuring (7). Financial hardship is a term used in corporate finance to describe a situation in which a promise made to a company's creditors is broken or is difficult to honor. Financial difficulties can sometimes lead to bankruptcy. Companies face financial difficulties as a result of poor management rather than economic stress. As a result, this condition is frequently accompanied by a comprehensive shift in organizational structure within management, governance, and structure. This organizational restructuring is thought to be capable of adding value by making better use of resources (7).

Information about a company's financial stress should be obtained as soon as possible so that financial pressure can be reduced and company bankruptcy avoided (8). From an academic standpoint, it was noted that the issue of financial distress in companies in various sectors in Indonesia was only begun to be studied in the 1990s and has only recently begun to develop in the 2010s. This research focuses on economic and financial literacy. This issue, in particular, has only recently gained traction in the textile and apparel industries (see figure 2).

This sector is becoming increasingly interesting to study, particularly in light of the Covid-19 pandemic, which is thought to have impacted a company's financial distress in most sectors (9–11). Previously, the textile and garment market conditions were quite depressed as a result of recent trade wars and pressure from producers from other countries, which resulted in price wars. In fact, the textile and garment sector, like other sectors, deteriorated during the Covid-19 pandemic, with the imposition of various activity restrictions and social distancing. However, this industry can make a comeback by repurposing its products as PPE (Personal Protective Equipment).

Twelve companies with positive working capitals are listed on the Indonesia Stock Exchange (IDX) in the textile and garment sub-sector (see table 1). This means that their assets are currently sufficient to pay their current debts. Meanwhile, the other four companies have negative working capital, which means that their assets cannot currently pay their current debts.

Table 1. Financial Condition of Textile and Garment Sub-Sector

No	Code	Name	Working Capital	Retained Earnings	EBIT	Equity Market Value	Book Value of Accounts Payable	Sales	Total Asset
1	BELL	Trisula Textile Industries Tbk	127.632.625.516	93.379.714.796	5.298.165.687	152.252.316.799	342.455.321.568	157.718.886.380	623.415.338.649
2	ERTX	Eratex Djaja Tbk	2.363.255	10.028.584	781.508	20.141.658	54.947.538	25.857.349	75.089.196
3	ESTI	Ever Shine Tex Tbk	2.478.019	- 68.752.787	- 314.357	13.242.371	44.552.056	7.874.088	57.794.427
4	HDTX	Panasia Indo Resources Tbk	- 255.163.118.000	- 1.885.029.188.000	- 31.818.676.000	38.641.899.000	380.770.657.000	3.106.084.000	419.412.556.000
5	INDR	Indo-Rama Synthetics Tbk	37.948.667	222.442.805	4.473.343	375.755.541	409.685.745	183.414.950	785.441.286
6	MYTX	Asia Pacific Investama Tbk	- 1.079.688.000.000	- 2.790.736.000.000	- 1.488.000.000	393.767.000.000	3.976.403.000.000	556.344.000.000	4.370.170.000.000
7	PBRX	Pan Brothers Tbk	451.860.472	104.863.229	577.386	264.785.076	358.934.916	121.655.179	623.719.992
8	POLY	Asia Pacific Fibers Tbk	- 964.421.693	- 2.197.054.069	5.036.195	- 937.041.585	1.175.393.696	87.430.962	238.352.111
9	RICY	Ricky Putra Globalindo Tbk	234.122.745.885	53.782.545.864	- 41.311.399.615	414.198.450.722	1.164.853.938.605	321.101.134.959	1.579.052.389.327
10	SRIL	Sri Rejeki Isman Tbk	734.588.589	425.663.319	30.595.135	622.213.737	964.227.176	316.615.378	1.586.440.913
11	SSTM	Sunson Textile Manufacture Tbk	103.601.114.061	- 158.702.126.267	4.829.720.353	203.912.975.724	254.294.612.854	103.379.499.739	458.207.588.578
12	STAR	Star Petrochem Tbk	489.592.894.190	10.186.266.478	171.018.912	490.187.186.456	90.160.937.202	507.489.524	580.348.123.658
13	TFCO	Tifico Fiber Indonesia Tbk	83.991.014	- 1.135.800	162.449	289.722.387	20.767.158	46.146.147	310.489.545
14	TRIS	Trisula International Tbk	350.717.840.963	93.919.539.165	9.622.432.981	667.326.876.574	591.202.232.510	344.044.704.395	1.258.529.109.084
15	UNIT	Nusantara Intri Corpora Tbk	- 583.833.331	26.625.473.166	325.321.502	246.979.605.182	117.068.678.736	39.799.921.556	364.048.283.918
16	ZONE	Mega Perintis Tbk	123.708.594.686	123.095.971.790	- 4.353.662.417	287.000.016.096	326.224.476.162	107.930.377.662	613.224.492.258

Source: Adopted from IDX. data, 2020

The company's health is important for increasing efficiency in running its business so that the ability to earn profits can be increased while avoiding the possibility of bankruptcy (liquidation) in the company. The occurrence of liquidation or bankruptcy in several companies will, of course, result in a number of issues involving the owners and employees who lose their jobs.

This phenomenon encourages researchers to investigate the most recent trends in financial distress research, particularly in Indonesia's textile and garment sub-sector. This study, in particular, has several goals, including analyzing the "framing" of financial distress research in the textile and garment sector, particularly in terms of research scope and methodology. Furthermore, this article attempts to systematically analyze the network formed by these literatures.

There appears to be no systematic review of the literature by Indonesian researchers in this field, especially given that this research also experimented with text mining and network analysis methods. This study's findings are expected to provide a comprehensive picture of the most recent developments in the study of financial distress in Indonesia, particularly in the textile and garment sub-sector. Furthermore, this paper can be used as a reference for practitioners who want to know what approaches and methods academics and practitioners have used to predict financial distress in Indonesian companies.

2. LITERATURE REVIEW

2.1 Financial management dan financial distress

Financial management is all activities or company activities related to how to obtain working capital funding, use or allocate funds, and manage assets owned to achieve the main goals of the company. The main purpose of financial management is to maximize the value owned by a company or to add value to the assets held by the shareowner (12–14). Predicting the survival of the company is very important for management and company owners to anticipate the possibility of potential bankruptcy. Financial distress itself is a condition in which the company's finances are in an unhealthy state or a crisis that occurred before bankruptcy. Bankruptcy itself is usually defined as a situation or situation where the company fails or is no longer able to fulfill the debtor's obligations because the company experiences insufficient and insufficient funds to run or continue its business (1,15–17). The financial distress model needs to be developed because knowing the company's financial distress from an early age is expected to take actions to anticipate that it will lead to bankruptcy.

2.2 Text mining and content analysis

This research also makes use of a text mining technique known as Knowledge Discovery in Databases (KDD). This method was chosen because the primary source of data was text-based scientific articles. This method is divided into two stages, the first of which is the processing and integration of unstructured data. Second, statistical data generated by text content extraction are analyzed (18). Meanwhile, the network analysis method, which is part of the Social Network Analysis, is used to visualize the relationships (edges) between words (nodes) using graphical software. The output of the engine analysis (in this case, the AntConc, RStudio, and Gephi software) is then interpreted using content analysis, which can dissect data statistics in great detail (19).

2.3 Literature review

The literature review approach in this study uses literature based on the Litmaps search engine. A critical analyzing method is then used in dissecting the topic of financial distress through various bibliographies (20–22). This approach is quite popular and has been used in various fields (19,23–26).

3. METHODOLOGY

In this study, a qualitative approach (27) was used through the literature review method (20–22). The text mining method is specifically adopted to study literature in the form of text (18,28) gathered through a web-scraping technique on Litmaps database with the keyword “financial distress” on “textile and garment” sector, with context boundaries in Indonesia (see image 2). This stage is followed by extracting article information in the form of text which is useful from the aspects of research scope and methodology (18,29–33). Furthermore, AntConc software is used to generate an output in the form of term frequency, clusters/N-grams, and word cloud through RStudio software (34,35). Data output is then used as nodes and edges for network analysis purposes (36–38) using Gephi software and qualitative content analysis (19). While the source of the case study data comes from the IDX, with the purposive sampling method (39,40) on the financial statements of the textile and garment sub-sector companies in 2019 and the first quarter of 2020.

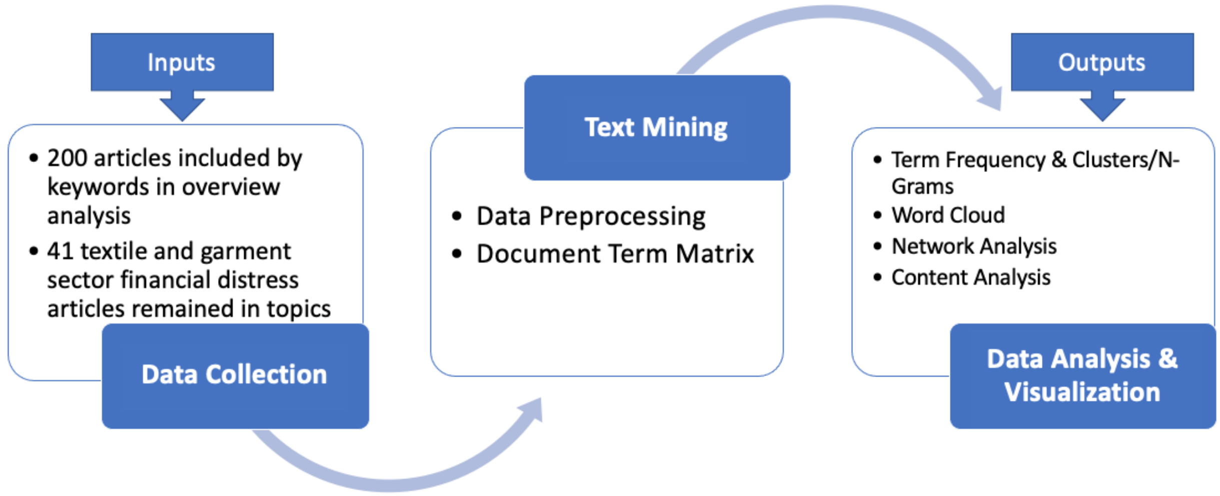

Figure 1. Research framework based on literature review
Source: The author's own study, 2021

3.1 Data collection

The corpus of this research was built using a web-scraping technique which was selected using identified keywords (24) from 200 articles to 41 articles specifically concerning financial distress in the textile and garment sector (see figure 2). The data collected and tabulated include aspects of research scope and methodology, which are then stored in text format (txt.) for text mining, analysis, and visualization processes.

3.2 Text Mining

To identify patterns or information, data collection is then explored and analyzed through two stages; data pre-processing and document term matrix (DTM) (41,42). For the first stage, data pre-processing is conducted through data cleaning, data integration, data transformation, tokenization, and normalization (35,43). The second stage is building DTM that identifies word frequency or token and clusters based on text data (corpus) that are ready using the AntConc device (44,45).

The processed text data (DTM) is then visually represented as a Word cloud. The RStudio tool is then used to illustrate the frequency of appearance of words on scales that are grouped by topic and aspect. The corpus used was classified based on the scope and methodology of the financial distress research. The following are the commands used to generate data.

```
#Generate the Word cloud
set.seed(1234)
wordcloud(words=d$word,freq = d$freq, min.freq = 3,max.words = 70, random.order = FALSE, rot.per = 0.65,colors = brewer.pal(6,"Dark2"))
```

Word cloud has a minimum word frequency of 3 and a maximum number of words displayed randomly of 70.

3.3 Data analysis and visualization

Term frequency review results found that a total of 994 words list (token) treated as Nodes, with the highest frequency (257) is perusahaan (company) and the lowest (1) being usaha (effort). While n-grams tools can scan the entire corpus to classify the word 'n' used to find common expressions in the corpus (44). Each n-gram showed in this research uses a size range of 2 at minimum and maximum (word count). This review has found 2.383 pairs of (n-gram) treated as Edges for network analysis processes, such as financial-distress, textile-garment (tekstil-garmen), company-textile (perusahaan-tekstil), stock-exchange (bursa-efek), and registered-stock (terdaftar-bursa).

The word cloud designed using the RStudio device (Team, 2013) is aimed to visualize the frequency of occurrence of words freely based on a scale based on research scope and methodology (33,35). While the network analysis is conducted in several stages such as visualization, exploration, and manipulation of a network of words (token) using the Gephi software or open-source application (38,46). Statistical calculations in this analysis include network properties, such as Average Degree Distribution, Network Diameter, average path length, and modularity (47).

Content analysis is then conducted to interpret and describe the pattern of frequency and correlation that has been visualized through RStudio and Gephi tools. This analysis is supported by several references related to financial distress in the textile and garment sector.

4. RESULT AND DISCUSSION

4.1 Corpus profile

Figure 2 shows that the literature on financial distress began to be collected in the early 1990s, or in 1991. This trend has accelerated since 2010 and continues to this day (2021). While statistics from the textile and garment industry show that literature began to be recorded in 2009 and increased in 2014. This distribution demonstrates that academics and practitioners are becoming more aware of the significance of the financial distress issue. Given the development of a relatively new issue in Indonesia, compared to the beginning of the global discussion (in 1966) (2), it is very interesting to examine the context and approach that is frequently used by Indonesian researchers and practitioners in relation to the issue of financial distress in the textile and garment industries.

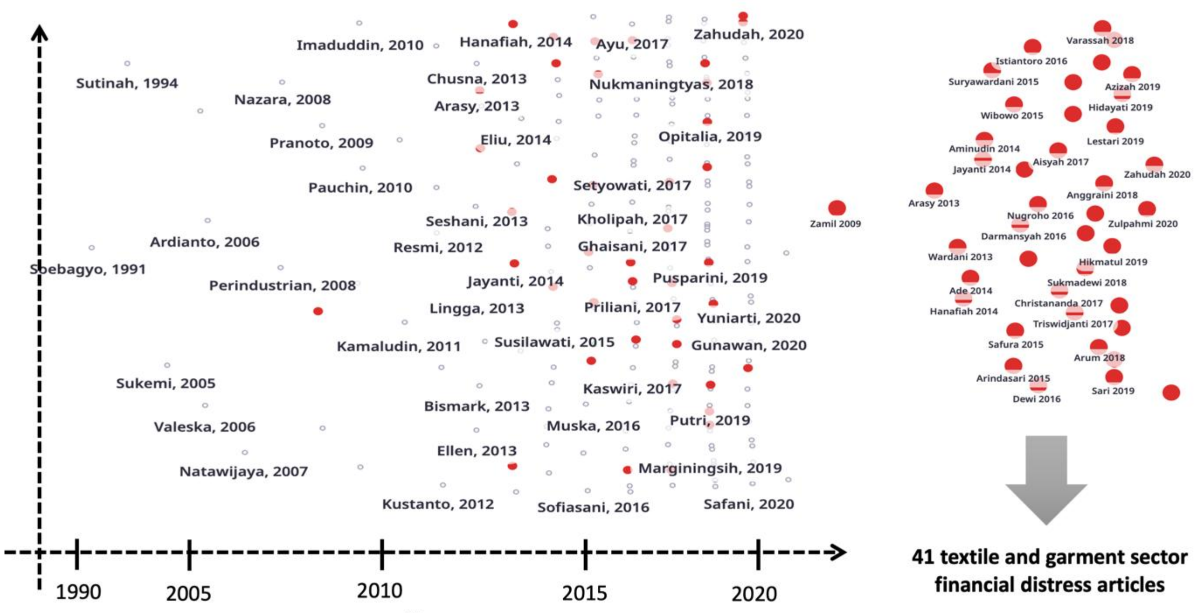

Figure 2. Trends in the distribution of financial distress literature between the general sector, textiles, and garments from 1991-2021
Source: Litmaps database, 2021

4.2 The recent trend of textile and garment sector financial distress study

Furthermore, this study employs 41 financial distress works of literature on the textile and garment sector as a corpus to be examined in terms of research scope and methodology. Based on the corpus, the text mining process generates word frequency or DTM. The most frequent occurrence is regarded as the most frequently discussed issue, and it serves as the main framing of the topic of financial distress in the textile and garment sector. DTM will be used as input in the network analysis process, in addition to reviewing the most frequently discussed issues.

4.3 Financial distress research scope and methodology in the textile and garment sector

The word list statistic results based on the aspects of research scope and methodologies (see Figure 3) show that the two are related. This means that the approach used in the literature is closely related to the issues or cases discussed based on article titles. This argument is supported by the calculation of term frequency which shows that the 20 tokens with the highest frequency in the research scope aspect include perusahaan (company, 37), tekstil (textile, 35), distress (30), financial (30), terdaftar (registered, 28), bursa (exchange, 27), efek (stock, 27), garmen (garment, 27), Indonesia (27), analisis (analysis, 23), studi (study, 19), score (16), memprediksi (predict, 15), periode (period, 15), altman (14), model (13), pengaruh (impact, 13), prediksi (prediction, 11), rasio (ratio, 11), and sektor (sector, 11). While from the methodology aspect there are penelitian (research, 65), perusahaan (company, 53), metode (method, 43), data (41), sampel (sample, 41), analisis (analysis, 32), teknik (technique, 30), tekstil (textile, 30), score (29), garmen (garment, 27), sampling (21), model (20), purposive (19), altman (17), bursa (exchange, 16), efek (stock, 16), Indonesia (16), terdaftar (registered, 16), distress (15), and keuangan (finance, 15).

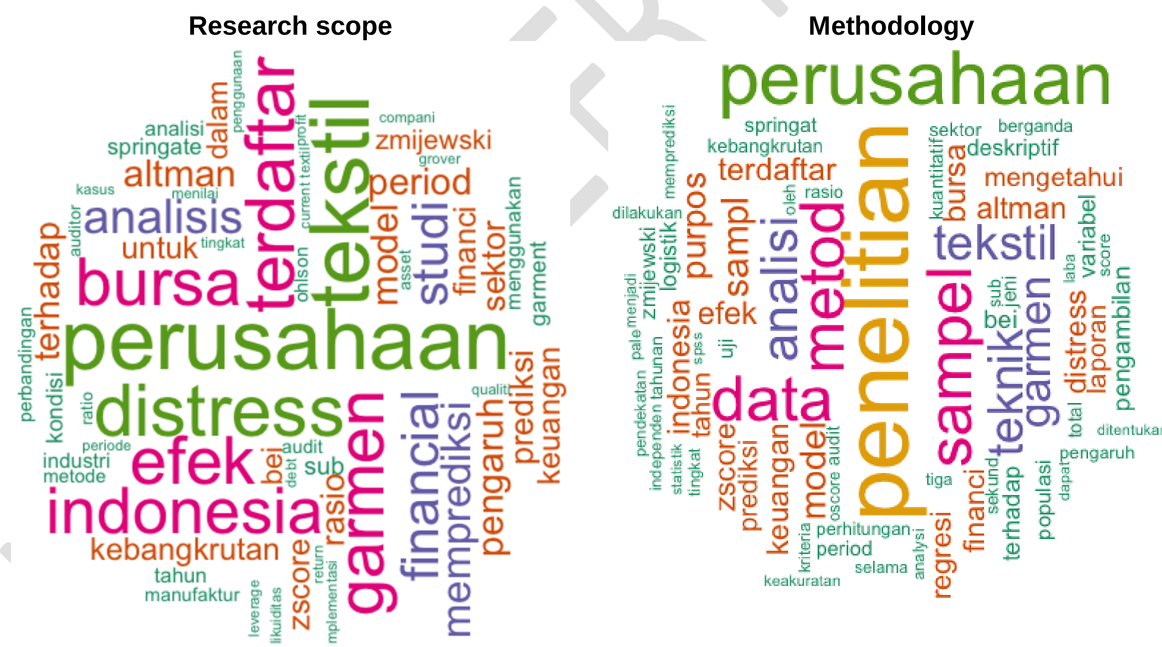

Figure 3. Research scope and methodology word cloud result
Source: R-studio-based data analysis, 2021

Word cloud shows that most of the literature examines the effect of financial variables, both dependent and independent, on the prediction of financial distress or vice versa. Some of the financial variables that appear frequently include rasio keuangan (financial ratio), kualitas laporan keuangan (quality of financial reports), return saham (stock returns), good corporate governance, rasio likuiditas (liquidity ratio), rasio aktivitas (activity ratio), rasio profitabilitas (profitability ratio), rasio leverage (leverage ratio) , perputaran piutang (accounts receivable turnover), solvabilitas (solvency), rasio hutang (debt ratio), komisaris independent (independent commissioner), struktur kepemilikan institusional (institutional ownership structure), Total Assets Turnover (Tato), Operating Profit Margin (Opm), opini auditor (auditor's opinion), Current Ratio, Net Profit Margin, and arus kas (cash flow). Meanwhile, other literature also states that financial distress can moderate the influence of various dependent variables. In addition, almost every piece of literature uses financial statements of textile and garment companies listed on the Indonesian stock exchange as case studies.

As for the methodology aspect, the word cloud shows that the approaches used are quite varied. Although most have adopted a quantitative approach, the models used to predict bankruptcy are very diverse, such as the Ohlson Score model (o-score), Altman Z-Score, Grover, Springate, zmijewski, Zavgren (Logit). Meanwhile, the analysis technique used includes multiple linear regression analysis, logistic regression, panel data regression, and quantitative descriptive, utilizing Statistical Package for the Social Sciences (SPSS) tool.

4.4 Systematic network analysis of financial distress review in textile and garment sector

Based on a statistical analysis review of network properties, the average degree distribution and average weighted degree values generated in the financial distress dataset in the textile and garment sector are 4.795 and 4.978, respectively. That is, as the value increases, it can be assumed that the number of connections one node has to other nodes on a network improves. Network Diameter (47) or the measurement used to detect the diameter in the text network with the measurement technique to find nodes with the most distant relationship, shows a value of 15 with a radius of 1, and the average distance between nodes or the average path length (47) is 4.035 (47). Meanwhile, the Modularity and Modularity resolution score calculations both show the number 0.500 with the number of communities or clusters in the network as many as 20. Yifan Hu's layout was chosen as the network analysis visualization model in this study, with 994 nodes and 2.383 edges of the relationship between nodes.

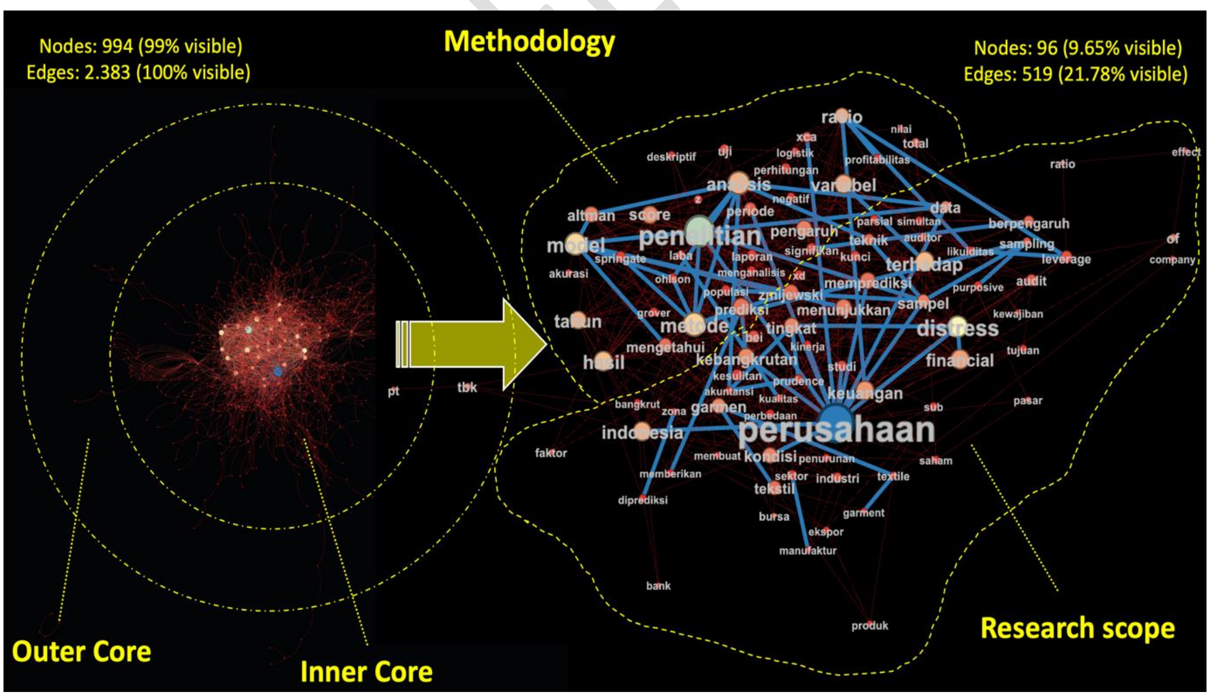

Figure 4. Network analysis of financial distress review in textile and garment sector
Source: Gephi-based data analysis, 2021

Figure 4 depicts a network analysis review of node relationships, which are clustered into two networks, an inner core and an outer core. The inner core is made up of clusters with the highest node occurrence frequency and edge weight. This is the main frame on the subject of financial distress in textile and garment companies. Clusters with a low node occurrence frequency and smaller edge weights, on the other hand, are classified as the outer core. In short, the outer core can be characterized as a zone of discourse with little or no relevance to this topic. The network analysis results also show that the inner core network is made up of research scope and methodology aspects. The weights of the nodes and edges of these two aspects can be seen in the size or scale of the circle, line, and font. The larger the circle and font visualization, as well as the thickness of the line connecting the nodes, the greater the weight or degree. In other words, large-scale nodes and edges indicate issues that are central to the framing or are frequently discussed in the context of financial distress in textile and garment companies. The relationship between nodes is also confirmed by providing labels for nodes, which are displayed as token identities on visualization.

This study discovered a link between word cloud output and network analysis. Despite the fact that the two frequently depict the same framing, network analysis has the advantage of visualizing the relationship between the issues being discussed. This output contributes significantly to the data interpretation. From the standpoint of research scope, this review demonstrates a correlation pattern that exemplifies the relevant discussion with the impact of financial variables on the prediction of financial distress, or vice versa. Financial ratios, stock returns, liquidity ratios, activity ratios, profitability ratios, leverage ratios, debt ratios, auditors' opinions, and current ratios are some of the dependent and independent financial variables that frequently appear and are interconnected. According to the majority of the literature, financial stress is a stage in which the company's financial condition deteriorates, which begins with liquidity difficulties experienced by the company and, if allowed to continue, leads to company bankruptcy. As case studies, they frequently use the financial statements of textile and garment companies listed on the Indonesian stock exchange. This is understandable given that the Indonesia Stock Exchange (IDX) is a party that organizes and provides a legal system and amenities to bring together Stock transaction activities of other parties in order for them to trade Stocks.

In terms of methodology, the network analysis reveals a few commonly used approaches, including the Ohlson score (o-score) model, Altman z-score, Grover, Springate, and Zmijewski, as well as multiple linear regression analysis techniques and the use of SPSS tools. Pozzoli (2) contended that the aforementioned models have their own characteristics. He stated that the Ohlson score (1980) and Zmijewski (1984) were created for a variety of reasons, including analyzing binary dependent variables, assisting in the development of non-linear regression models with the cumulative distribution function assumption, providing company financial distress probability and significance predictor, and not requiring any assumptions regarding distribution predictor. While the Altman model (1968) examines two or more variables at the same time and assumes a multivariate normal distribution and variance-covariance metrics. This function is then used to justify the use of the Z-score method in the analysis of this research case study. The Beaver model (1966), Deakin (1972), Edmister (1972), Moyer (1977), Zavgren-Logit (1985), and Holmen (1988) are theoretical models that have not been widely used by this corpus (2).

5. CONCLUSION

This study concludes that, while the issue of financial distress in the textile and garment sector is still relatively new, it has piqued the interest of many academics and practitioners. Furthermore, based on the research scope and methodology, this study discovered that the dominantly discussed topic is related to the impact of financial variables, which are either dependent or independent of the prediction of financial distress, or vice versa. The most common approach is quantitative, and it employs various models of financial distress. This phenomenon demonstrates how academics and practitioners in Indonesia are still searching for the right formula to predict financial distress, particularly in cases involving textile and garment sector companies. The network analysis result, which shows a positive correlation between word cloud outputs and network analysis, supports this conclusion. Despite the fact that the two frequently have the same framing, network analysis has the advantage of being able to visualize the correlations between the issues being discussed. This output has a significant impact on data interpretation.

The corpus aspect of this research is limited, and the research scope is limited to the Indonesian context. Future research with broader literature sources and different types of company sectors is highly anticipated. This study's systematic review of the literature can at least provide a comprehensive framework for the issue of financial distress in Indonesian textile and garment sector companies. Furthermore, this is a recent study that conducts a systematic review of the literature on financial distress in Indonesian textile and garment companies.

COMPETING INTERESTS DISCLAIMER:

Authors have declared that no competing interests exist. The products used for this research are commonly and predominantly use products in our area of research and country. There is absolutely no conflict of interest between the authors and producers of the products because we do not intend to use these products as an avenue for any litigation but for the advancement of knowledge. Also, the research was not funded by the producing company rather it was funded by personal efforts of the authors.

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