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Mix

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COMPARATIVE ASSOCIATION RULES TO FIND AN EFFECTIVE FISCAL POLICY MIX

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Abstrak

Pada tahun 2021, pemerintah Indonesia melakukan revisi APBN sebanyak empat kali. Dinamika lingkungan sosial ekonomi begitu cepat berubah berimplikasi pada kompleksitas pembuatan kebijakan yang dituntut cepat pula. Kebijakan yang diambil cenderung dipengaruhi oleh naluri pimpinan berdasarkan data yang tidak holistik sehingga sangat mungkin terjadi kebijakan yang tidak tepat. Tujuan dari penelitian ini adalah untuk membandingkan apriori, FP-Growth, dan EClAT untuk menemukan algoritma terbaik dalam merumuskan bauran kebijakan fiskal yang efektif berdasarkan data historis. Kajian ini menggunakan dataset tahun 2021, yang mencakup 19.166 record kebijakan yang disusun berdasarkan Satuan Kerja. Penelitian ini menggunakan pendekatan *Knowledge Discovery in Databases* (KDD). Kesimpulan penelitian yaitu algoritma FP-Growth adalah algoritma terbaik untuk menemukan bauran kebijakan yang efektif. Algoritma FP-Growth dengan $\text{minlen} = 7$ mencapai nilai kinerja anggaran terbaik sebesar 96,77. Sementara itu, algoritma apriori dapat diandalkan untuk merumuskan kebijakan fiskal yang selaras antara manajemen puncak dan manajemen menengah. Algoritma EClAT memiliki keunggulan dalam mengidentifikasi mayoritas kebijakan fiskal yang akan diambil oleh manajemen menengah.

Kata kunci: Apriori Algorithm, FP-Growth, EClAT, Fiscal Policy

Abstract

In 2021, the government of Indonesia change the way it spends money four times. The dynamics of the socio-economic environment, which changes so quickly, has implications for the complexity of policy making, which is demanded immediately. The policies taken tend to be influenced by the instincts of the leadership based on non-holistic data, so inappropriate policies are very likely to occur. The aim of this study is to compare a priori, FP-Growth, and EClAT to find the best algorithm for formulating an effective fiscal policy mix based on historical data. This study use the 2021 dataset, which includes 19,166 policy records organized into Work Units. This study uses the Knowledge Discovery in Databases (KDD) approach. Our conclusion is the FP-Growth algorithm is the best way to find effective policy mix. FP-Growth algorithm with $\text{minlen} = 7$ reach the best budget performance scores at 96.77. Meanwhile, the apriori algorithm can be relied upon to formulate a fiscal policy that is aligned between top management and middle management. The EClAT algorithm has the advantage of identifying the majority of fiscal policies that will be taken by middle management.

Keywords: Apriori Algorithm, FP-Growth, EClAT, Fiscal Policy

I. INTRODUCTION

Before the COVID-19 pandemic, Indonesia's economic growth was quite good, during the 2010–2019 period, it averaged 5.41 percent per year. When the COVID-19 pandemic peaked in 2020, Indonesia entered a recession, slowing growth by 2.97 percent. Studies [1] state that a pandemic will have a negative impact not only on individual health, but also on a country's economy. The

Indonesian government carried out a combination of policies in the economic sector to restore the economy. In 2020, Indonesia will implement an expansionary fiscal policy to accelerate economic growth and increase aggregate demand. However, expansionary fiscal policy has a negative impact, namely increasing the fiscal deficit and fiscal risk [2]. The Indonesian government took an extreme step by loosening the deficit policy to exceed three percent of GDP until 2022. In an effort to stabilize the economy, fiscal policy interacts with monetary

policy as described by the Chugh model based on the dynamic equilibrium approach [3]. Measuring the implications of fiscal policy shocks can be done using vector autoregressive (SVAR, VAR, and BVAR) models [4]. However, this measurement is only limited to macroeconomic variables. In 2021, the government of Indonesia will change the way it spends money four times. The dynamics of the socio-economic environment, which changes so quickly, has implications for the complexity of policy making, which is demanded immediately. The policies taken tend to be influenced by the instincts of the leadership based on non-holistic data, so inappropriate policies are very likely to occur.

The Indonesian Ministry of Finance is now using a research paradigm to implement policy. Policy making based on research methods, especially data mining. Understanding the hidden patterns of data can help make the right decisions, especially during critical conditions [5]. One alternative for understanding data is through association rules. Based on our literature review, there are 5 articles discussing apriori algorithm, 6 articles discussing Frequent Pattern Growth (FP-Growth) algorithm, and 8 articles discussing Equivalence Class Transformation (EClat) algorithm. These findings indicate that algorithms are the most popular topic for research because of their ease of implementation in various fields. An apriori algorithm uses a repetitive approach to find associative relationships between itemsets based on Boolean association rules. Apriori algorithms are generally applied using market basket analysis for product layout management [6], motorcycle sales [7], clinical data mining [8], and consumer behavior [9]. The FP-Growth algorithm is a refinement of the a priori algorithm, which uses the FP-Tree data structure to generate significant frequent itemsets [10]. The application of the FP-Growth algorithm is focused on the fields of power marketing analysis [11], handling big data [12], region-based discovery in the IoT environment [13], retail sales [10], [14], and determining student interest in fields of study [15]. While EClat has a different approach because it uses a depth-first search approach with vertical datasets. EClat has four variations: post-diffset, diffset, tidset, and sort-diffset [16]. In previous studies, EClat was applied to determining borrowing patterns for books [17], finding future income patterns [18], inventory management [19], and microbial association networks [20].

The aim of this study is to compare a priori, FP-Growth, and EClat to find the best algorithm for formulating an effective fiscal policy mix based on historical data. Previous association rule research tends to lead to improvements to the algorithms used, such as MANIEA [20], ETPAM [21], i-Eclat [22], R-Eclat [16], whale optimization algorithm [23], and the frequency-based Efficient Web Mining (FBWM) algorithm [24]. This research focuses on the use of basic algorithms for comparison. For comparison, the research we found mostly compares two algorithms in studies [9], [14], and [18], while this study will compare three algorithms. In addition, this research uses real data from the government sector, which we have not found in previous studies. The results of the research will be a reference for policy makers as material for consideration in decision-making.

II. METHODOLOGY

A. Data sources and Research Variables

This study uses the 2021 dataset, which includes 19,166 policy records organized into Work Units with three main policy groups: expenditure revision policies, financing policies, and budget blocking policies. The policy for revising expenditures involves adding and subtracting personnel, goods, and capital expenditures. The allocation of sources of financing, such as the counterpart fund, non-tax state revenue, grants, and loans, is governed by the financing policies. The budget blocking policy comprises of blocking personnel, goods, and capital expenditures.

B. Research Framework

This study uses a comparative study approach to determine the best association rule algorithm. This study uses the Knowledge Discovery in Databases (KDD) approach. KDD is a process that involves extracting useful, previously unknown, and potentially valuable information from large data sets. The purpose of the KDD process is to find potential data taken from the database, which will later be studied through patterns and then analyzed and visualized so that it is easily understood by users. Figure 1 shows five stages to obtain conclusions: data selection, data preprocessing, data transformation, data mining, and interpretation/evaluation.

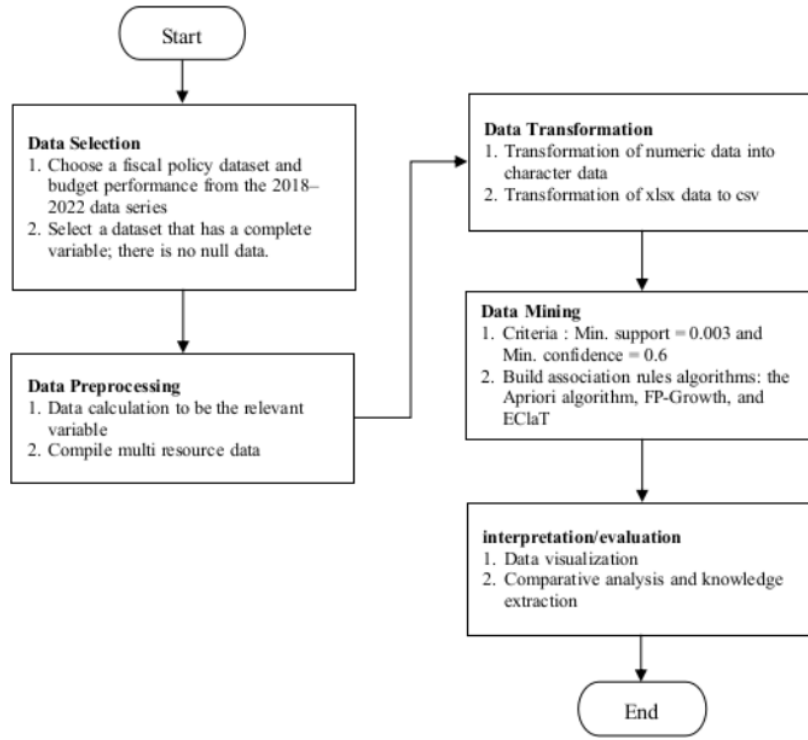


Figure 1. Research Framework

Before making an association rule algorithm, we must first figure out the support and confidence values. The support value is formulated by Formula (1):

$$S(x \rightarrow y) = \frac{|\{t \in z | x \cup y \subseteq t\}|}{|z|} \quad (1)$$

In which x is the antecedent of the rule in itemset form; y is the consequent in itemized form; t is a transaction containing x and y ; and z is the total transaction. the sum of the itemset distribution with eight policies for one record is 74 with a total of 19,166 records, thus we set a support value of 0.003. This value is obtained from. We do a round down so that more rules are formed. Confidence value indicators need to be set to support. The confidence value is calculated using the Formula (2):

$$C(x \rightarrow y) = \frac{|\{t \in z | x \cup y \subseteq t\}|}{|\{t \in z | x \subseteq t\}|} \quad (2)$$

Study [25] applies a confidence value of 0.5 to a total of 685 transactions. This study uses a

larger dataset, so the confidence value used must be higher. We apply a confidence value of 0.6.

Formula (3) shows the Apriori algorithm formula as follows [25]:

$$\text{Apriori}(T, \text{minsup}) = \bigcup_{k=1}^{\infty} F_k \quad (3)$$

In which T is the transactional database, minsup is the minimum support threshold, and F_k is the set of frequent k -itemsets. Then, for FP-Growth formula shows by Formula (4) [26].

$$\text{FP-Growth}(T, \text{minsup}) = \bigcup_{X \in F_1} \text{FP-Growth}(T | X, \text{minsup}) \cup \{X\} \quad (4)$$

Where F_1 is the set of frequent 1-itemsets, and $T|X$ is the conditional database for itemset X . Formula (5) shows the EClAT algorithm formula [26].

$$\text{Eclat}(I, T, \text{minsup}) = \bigcup_{i \in I} \text{Eclat}(I_i, T_i, \text{minsup}) \cup \{i\} \quad (5)$$

where I is the set of items, minsup is the minimum support threshold, I_i is the set of items that share a common prefix with item i , and T_i is the set of transactions that contain item i .

III. RESULTS AND DISCUSSION

A. Result

1. Data Selection

The dataset used in this study contains data on expenditure revision policies, financing policies, budget blocking policies, and budget performance. The data on expenditure revision policies comes from data on personnel, goods, and capital expenditures in the OMSPAN application, which consists of data at the beginning of the year and at the end of the year. Data financing policies based on budget funding data for each Work Unit in the OMSPAN application. This budget's funding consists of counterpart funds (RM), foreign loans (PLN), Rupiah viability gap funds (RMP), non-tax state revenue (PNBP), domestic loans (PDN), public service agency budget (BLU), foreign grants (HLN), domestic grants (HDN), foreign direct grants (HLL), Government Islamic Securities (SBSN). Meanwhile, data on budget blocking policies originates from data on personnel, goods, and capital expenditure budgets that cannot be used (blocked) throughout the current year. For budget performance, use results from calculations of indicators of budget absorption, consistency of plans for withdrawing funds, achievement of output, and efficiency. The data is sourced from the SMART application. After these data were collected, a dataset was selected from the 2018–2022 time series data. We chose the 2021 dataset because the available data is the most complete, has been verified by external auditors, and describes fiscal policy during the post-recession recovery period. We obtained 19,445 verified records for further processing.

2. Data Preprocessing

From the results of the data selection, we get 19,445 records. Then, we do some computation on the data to get it ready. First, to get data on expenditure revision policies, data from the end of the year are subtracted from data from the beginning of the year. The difference (range) between these two numbers indicates the amount of revised expenditure for a year. The arithmetic operations are also performed on data budget blocking policies. Second, for data financing

policies, the data value "0" is replaced with null. This is so that the association rule algorithm does not misinterpret the data. Third, the calculation of budget performance scores is based on indicators of budget absorption, consistency of plans for withdrawing funds, achievement of output, and efficiency. Fourth, we compile the data to produce the records that will be used. In this phase, we found 279 Work Unit records that did not have a budget performance score, then 19,166 records for further processing.

3. Data Transformation

The data that has been collected is still in the form of numerical data. To improve the performance of the association rule algorithm, study [5] suggests transforming numerical data into categorical data. The first transformation carried out on budget performance score is shown in Table 1. The classification of budget performance score in Table 1 is based on Ministry of Finance Regulation Number 22/PMK.02/2021.

Table 1. Budget Performance Score Transformation

Budget Performance Score	Data Transformation
> 90	Excellent
80 - 90	Very Good
60 - 80	Good
50 - 60	Fair
< 60	Poor

Data transformation is also carried out on expenditure revision policies, financing policies, and budget blocking policies. Each funding allocation will be transformed according to the funding source code. If the type of funding is not available in a work unit, it will be considered null data. This funding budget consists of counterpart funds (f.RM), foreign loans (f.PLN), Rupiah viability gap funds (f.RMP), non-tax state revenue (f.PNBP), domestic loans (f.PDN), public service agency budget (f.BLU), foreign grants (f.HLN), domestic grants (f.HDN), foreign direct grants (f.HLL), Government Islamic Securities (f.SBSN). As for the data transformation of expenditure revision policies and budget blocking policies, it is shown in Table 2.

The dataset is presented in two CSV files. This separation is done to adjust the required dataset for each association rule algorithm. The first file is prepared for use in the a priori and EClAT algorithms. While the second file is used in the FP-Growth algorithm.

Table 2. Budget Policy Transformation

<i>General Policy</i>	<i>Subpolicy</i>	<i>Symbol</i>
Revision policy	Increase personnel expenditure	a.51
	Decrease personnel expenditure	s.51
	Increase goods expenditure	a.52
	Decrease goods expenditure	s.52
	Increase capital expenditure	a.53
	Decrease capital expenditure	s.53
	Increase social assistance expenditure	a.57
	Decrease social assistance expenditure	s.57
Budget Blocking Policy	Increase blocking personnel expenditure	a.Block51
	Decrease blocking personnel expenditure	s.Block51
	Increase blocking goods expenditure	a.Block52
	Decrease blocking goods expenditure	s.Block52
	Increase blocking capital expenditure	a.Block53
	Decrease blocking capital expenditure	s.Block53
	Increase social assistance expenditure	a.Block57
	Decrease social assistance expenditure	s.Block57

4. Data Mining

The data used to build the model consists of 19,166 records. The data has 26 columns and a density level of 0.1355365. The five items with the highest frequency are fRM (19,083), s.52 (12,565), s.51 (8,094), a.51 (6,511), and fPNBP (4,514). The

minimum value of item-set/transaction is one. The maximum value of itemset/transaction is ten. The item set with the greatest support is fRM. With a minimum support of 0.003 there are 18 itemsets. All data has a character class.

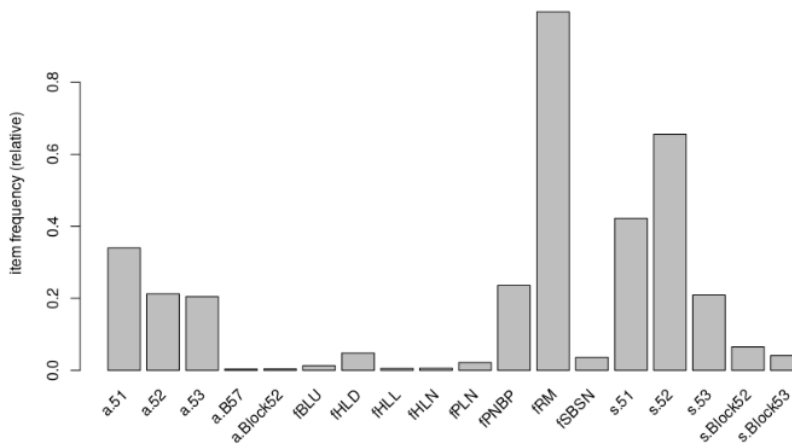


Figure 2. Item frequency with minimum support 0.003

In the next step, we use three algorithms—the apriori algorithm, FP-Growth, and Eclat—to build association rules. The transformed dataset will be processed using three association rule algorithms. If we only use the apriori algorithm in the rules library, there is the potential for redundant rules. To overcome this, we use the !is.redundant() syntax. Experimental results using a dataset that is fiscal

policy show that the apriori algorithm can find rules for an itemset with a maximum value of seven. The a priori algorithm cannot find a rule for an itemset with a value above seven. Taking into account the complexity of fiscal policy, we determine the rules to be used in the range of 5–7 itemsets for each rule that is formed. The a priori algorithm generates 117 rules for 5 itemsets; 24 rules for 6 itemsets, and 4

rules for 7 itemsets. The lift ratios are in the range 0.9338866–17.2212863. 1

The next algorithm is the FP-Growth algorithm. In the FP-Growth algorithm, there is a need to set a consequent, in this case, the budget performance value variable. The FP-Growth algorithm produces 652 rules for 5 itemsets; 1,627 rules for 6 itemsets, and 2,853 rules for 7 itemsets. The FP-Growth algorithm finds far more rules than the apriori algorithm. The lift ratios are in the range 1.222581–2.502377.

The third algorithm used is the Eclat algorithm. This algorithm uses the vertical intersection of the tidlist. This algorithm has the advantage that the tidsets represent support [27]. The Eclat algorithm generates 117 rules for 5 itemsets; 24 rules for 6 itemsets; and 4 rules for 7 itemsets. The resulting lift ratio is in the range 0.9338866–17.2212863. Quantitatively, the results of the Eclat algorithm are the same as those produced by the Apriori algorithm.

The three association rule algorithms that were built can find rules for one to seven itemsets. For eight itemsets, no single algorithm is able to find the rule. The results of the initial calculations for the three algorithms showed that the FP-Growth algorithm found the most rules, with a total of 2,853 rules for seven itemsets. While the Apriori and Eclat algorithms find the fewest rules with four

rules for seven itemsets. Lift ratios below one are found in the Apriori and Eclat algorithms. While the FP-Growth algorithm produces a lift value above one. These results indicate that all the rules found by the FP-Growth algorithm are strong and valid. The rules found by the Apriori and Eclat algorithms still have to be filtered again for those with a lift ratio of higher than one.

B. Discussion

5. Interpretation/ Evaluation

The association rule algorithm that was built has found a lot of rules that can be used by decision makers to make a mix of fiscal policies. To make it easier for decision makers, we filter the rules found. The parameters used to filter rules are a minimum of seven itemsets, a lift ratio higher than one, and ranking in the top three for each category. Table 3 shows the top three rules for each association rule algorithm with seven itemsets. The a priori and FP-Growth algorithms are sorted based on the lift ratio, while the Eclat algorithm is based on the confidence score. Sorting based on the confidence score of the Eclat algorithm to find the highest budget performance score of the rules found. For Apriori and FP-Growth the budget performance score is higher when sorted by lift ratio.

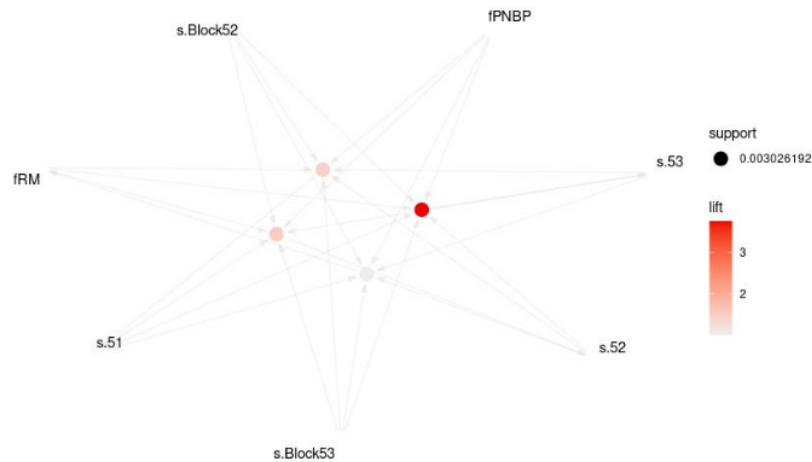
Table 3. Association Rule Algorithm Results

	lhs	rhs	support	confidence	lift	budget performance score (n_NKA)
Apriori algorithm						
minlen = 7						
[1]	{fPNBP, fRM, s.51, s.52, s.Block52, s.Block53}	{s.53}	0.0030	0.7838	3.7508	87.11
[2]	{fPNBP, fRM, s.51, s.53, s.Block52, s.Block53}	{s.52}	0.0030	0.9831	1.4995	87.11
[3]	{fPNBP, fRM, s.52, s.53, s.Block52, s.Block53}	{s.51}	0.0030	0.6042	1.4306	87.11
FP-Growth algorithm						
minlen = 7						
[1]	{f02=0, 51_rev=0, block52_rev=0, f04=0, 52_rev=s.52, f19=fSBSN}	{n_NKA=Excellent}	0.0031	0.9672	2.5024	96.92
[2]	{f02=0, 51_rev=0, block52_rev=0, 52_rev=s.52, f19=fSBSN}	{n_NKA=Excellent}	0.0032	0.9531	2.4659	96.77
[3]	{f02=0, 51_rev=0, f04=0, 52_rev=s.52, f19=fSBSN}	{n_NKA=Excellent}	0.0031	0.9524	2.4640	96.92
Eclat algorithm						

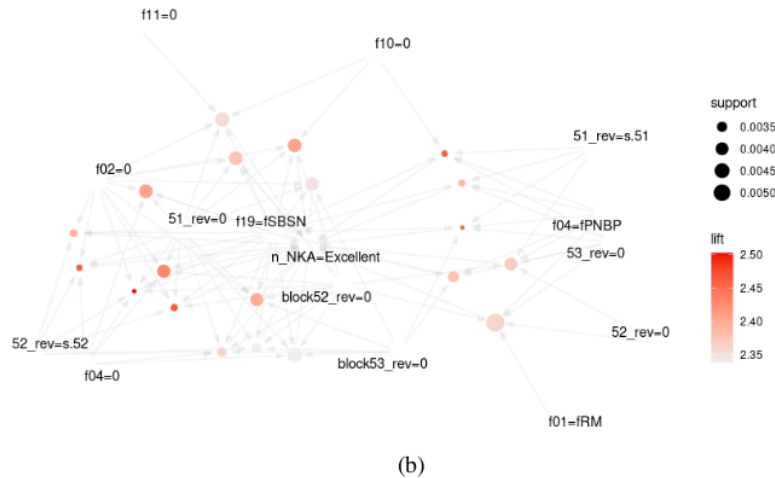
	lhs	rhs	support	confidence	lift	budget performance score (n_NKA)
minlen = 7						
[1]	{fPNBP, s.51, s.52, s.53, s.Block52, s.Block53}	{fRM}	0.0030	1.0000	1.0043	87.11
[2]	{fPNBP, fRM, s.52, s.53, s.Block52, s.Block53}	{s.51}	0.0030	0.6042	1.4306	87.11
[3]	{fPNBP, fRM, s.51, s.53, s.Block52, s.Block53}	{s.52}	0.0030	0.9831	1.4995	87.11

The apriori algorithm shows a much larger lift ratio than the other two algorithms. This algorithm has the advantage of finding rules between fiscal policy variables that have strong associations. The rule with the strongest association is found at minlen = 7, namely: IF allocate non-tax state revenue (fPNBP), allocate counterpart funds (fRM), decrease personnel expenditure (s.51), decrease goods expenditure (s.52), decrease blocking goods expenditure (s.Block52), decrease blocking capital expenditure (s.Block53) THEN decreasing blocking capital expenditure (s.53). However, the policy mix is not yet very effective in achieving a budget performance score, the rules

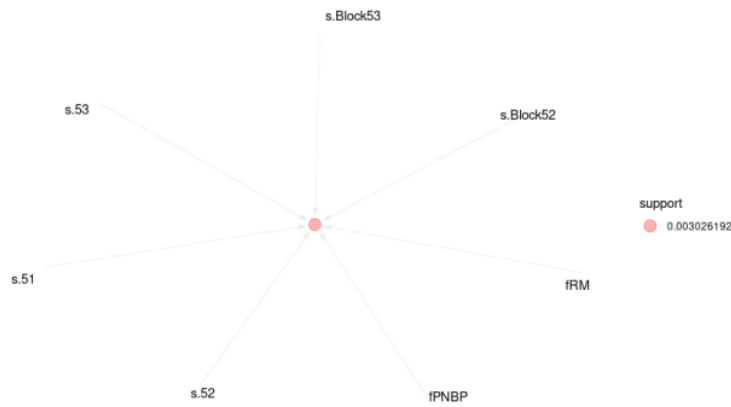
found only reach the "Very Good" criteria (80–90). At minlen = 7, the budget performance score achieved the best score at 87.11. Figure 3 (a) shows that at minlen = 7, only involves seven variable but reach greater lift ratio than other algorithm. The knowledge gained from the apriori algorithm focuses on the actions and reactions of fiscal policy choices taken by middle-level management. The rules found in this algorithm help top management understand the patterns that are formed when a fiscal policy is set so that it can formulate an effective fiscal policy.



(a)



(b)



(c)

Figure 3 Apriori algorithm with minlen = 7 (a); FP-Growth algorithm with minlen = 7 (b); EclAT Algorithm with minlen = 7 (c).

The FP-Growth algorithm's results show that there is a mix of fiscal policies that can lead to a high budget performance score. The FP-Growth algorithm is able to find a fiscal policy mix that produces a budget performance score that meets the "Excellent" criteria. Figure 3 (b) shows that the FP-Growth algorithm involves more variables than the other two algorithms. Knowledge that can be drawn from the results of this algorithm, especially for financing policies originating from debt. The results of this algorithm show that the policy of not allocating foreign loans (fPLN) and allocating Government Islamic Securities (fSBSN) can produce a high level of performance. These results can be considered by decision-makers to reduce dependence on foreign loans and direct them to Government Islamic Securities. For spending revision policies, the FP-Growth algorithm finds that not revising the

personnel spending budget and reducing material spending is a fiscal policy choice that can result in a high budget performance score. Reducing spending on goods is one of the strategies to cut bureaucratic costs so that available resources can be prioritized to achieve output. The rule findings from this algorithm can be used by decision-makers to formulate fiscal policies that maintain performance at an optimum level.

The EclAT algorithm finds the rule with the highest confidence compared to the other two algorithms. This algorithm finds rules that are supported by a high level of confidence and support. Figure 3 (c) shows that at minlen = 7, only involves seven variable and only one node. In terms of funding, the results of this algorithm show the association between the allocation of counterpart funds (f.RM) and non-tax state revenue (f.PNBP) to

reduce personnel expenditure (s.51) and goods expenditure (s.52). This finding can be used as a consideration for decision-makers in determining funding policies so that spending remains efficient. In terms of expenditure revision policy, the results of the algorithm found that the pattern of reducing personnel spending (s.51), reducing spending on goods (s.52), and reducing capital spending (s.53) has a strong association. In order to remain productive, decision makers need to consider the associative relationship between the three policies when formulating spending efficiency policies. This needs to be considered because the rules found by the EClAT algorithm produce an average budget performance score that is lower than the other two algorithms. The technical thing that should be considered when using this algorithm is the utilization of physical memory and processing time [28]. The EClAT algorithm helps decision-makers find patterns of policy actions that will be taken by the majority of middle-level management in responding to environmental changes.

Based on what the analysis found, each of the three association rule algorithms has its own pros and cons. The apriori algorithm excels at understanding the fiscal policy mix that will be chosen by middle-level management so that decision-makers can construct the right fiscal policy construction. However, this algorithm is not very good at achieving an optimum budget performance score. To overcome these weaknesses, decision-makers can use the FP-Growth algorithm. This algorithm is very good for finding rules that can achieve an optimum budget performance score. The problem with this algorithm lies in the fact that the support value for each rule that is found is generally quite low, so the rules that are found are like looking for hidden gems in a data set. The EClAT algorithm is an alternative algorithm to overcome low support values. Ironically, a high support value must be traded off for a low performance score. If you consider the trend of public demand for government performance, the FP-Growth algorithm is the best alternative for formulating fiscal policies that can achieve optimum performance.

IV. CONCLUSION

Based on the analysis, the FP-Growth algorithm is the best way to find association rules that get the best scores for budget performance. The highest budget performance score that can be achieved is 96.77 with FP-Growth algorithm at $\text{minlen} = 7$. One of the rules found is not to allocate foreign loans ($f02=0$), not to revise personnel expenditure allocations ($51_rev=0$), not to revise the amount of

blocking goods expenditure ($\text{block}52_rev=0$), to reduce spending on goods ($52_rev=s.52$), and allocate Government Islamic Securities ($f19=fSBSN$). Meanwhile, the apriori algorithm can be relied upon to formulate a fiscal policy that is aligned between top management and middle management. The EClAT algorithm has the advantage of identifying the majority of fiscal policies that will be taken by middle management.

The association rules found by the FP-Growth algorithm can be used as a fiscal policy database. The database is meant to be a resource for finding different ways to deal with changes in the economy. Researchers should be able to find a set of rules that sums up the three algorithms tested in this study in future studies. For further research, we recommend expanding the work unit attribute. Subsequent research can explore the attributes of the Work Unit's location, the amount of the Work Unit's budget, and the Major Project it owns.

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