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ASSOCIATION RULE MINING IN ANALYSIS OF THE RELATIONSHIP BETWEEN WORK ENGAGEMENT AND WORK LIFE BALANCE ON THE PERFORMANCE OF FEMALE LECTURERS

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Abstract: This study aims to determine the relationship pattern of Work Engagement and Work Life Balance on the performance of female lecturers. And in the context of science and technology, this study aims to develop the field of data mining studies regarding the ability of association rule mining techniques to the field of human resource management. This analysis uses independent variables, namely work engagement and work life balance. The dependent variable is the lecturer performance index. Respondents in this study were female lecturers who taught at Lancang Kuning University. This study uses the Association Rule Mining technique. Association rule mining is one of the techniques in data mining. Association rule mining has received great attention because of its use in a variety of research applications. The data used in data mining is in the form of historical data. The data was collected by means of a questionnaire. The results of this study can trigger the subject to create problem solving in performance management.

Keywords: work engagement, work life balance, lecturer perfomance, association rule

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1. Introduction

Based on Indonesian statistics in PDDIKTI about the number of researchers, female lecture are still fewer (43.60%) than male lecturers (56.40%). This is assumed to be one of the impacts of the condition that women are faced with high work and family pressures and are required to play an important role in both domains. Thus, the challenges and obstacles faced by female lecturers in their efforts to work and achieve careers outside the home tend to be more complex than men. The consistency of current performance is an obligation for lecturers. However, the fact that the workload is relatively high, the resources are varied, especially in terms of the various supporting capacities of facilities or infrastructure in each institutional unit tend to justify that the achievement of lecturer performance is relatively complex.
Lecturers in addition to carrying out the Tri Dharma as their main task, lecturers also carry out various additional tasks, for example, scientific activities, being consistent in achieving indexed publications (for example, indexed scientific publications of the Indonesian and international Citation and Indexing System), being involved in associations, or task forces or structural tasks. institutions (Dessy Balik, 2020). The fact that the high quantity of workload for female lecturers has the potential to cause boredom and require more enthusiasm is needed, so *work engagement* for female lecturers is needed. This is assumed to have an impact on a

tendency to decrease performance. Conversely, work-life balance will have an impact on *Work Engagement* which causes high motivation and is able to face every challenge in the work that leads to increased performance. The level of performance of lecturers is a form of lecturer involvement in supporting the preparation and realization of accreditation of private higher education institutions.

Each pattern of work engagement and work life balance of female lecturers with their level of performance as a lecturer has a different pattern of tendencies. This is influenced by several aspects. According to Schaufeli et al, (2002) indicators of work Engagement consists of aspects of spirit (vigor), dedication (dedication), and appreciation (absorption). According to Fisher, Bulger, & Smith, (2009) work life balance has four dimensions of work life balance caused by Work Interference Personal Life (WIPL), Personal Life Interference Work (PLIW), Personal Life Enhancement of Work (PLEW) and Work Enhancement of Work. Personal Life (WEPL) This research uses technique association rule mining. An association rule mining used to explore knowledge by searching rules which fulfil minimum support which and minimum confidence. An association rule mining is one of the techniques in data mining. An association rule mining get attention big because use in various applications researcher (Amir Mahmud Husein and Sriyuni Sinaga, 2019). The data used in data mining is in the form of historical data. Historical data is also known as training data or experience data. The results of an association rule mining in the form of knowledge or knowledge.

2. Literature Review

The theories that support this research are:

Work *Engagement*

Schaufeli et al., (2002) define *work engagement* as a positive, satisfying, work-related psychological condition characterized by enthusiasm, dedication, and appreciation. *Work engagement* indicators consist of three aspects, namely:

a. Spirit (*Vigor*)
b. Dedication (*Dedication*)
c. appreciation (*absorption*)

Work Life Balance

According to Greenhaus et al., (2003) *work-life balance* is defined as a work-life balance in which a person is tied in a balanced way between work responsibilities and family or life responsibilities.

According to Fisher, Bulger, & Smith, (2009) *work life balance* has four dimensions, namely:

a. *Work interference personal life (* WIPL)
b. *Personal life interference work (* PLIW)
c. *Personal life enhancement of work* (PLEW)
d. *Work enhancement of personal life* (WEPL)

Data Mining

Data mining has attracted a lot of attention in the world of information systems and in society as a whole in terms of data mining recent years, due to the widespread availability of large amounts of data and the immediate need to convert that data into useful information and knowledge (M. McLaren, 2012). The information and knowledge gained can be used for applications ranging from market analysis, fraud detection, and customer retention, to production control and science exploration (Han and Kamber, 2001).

According to Larose in his book which is Entitled "*Discovering Knowledge in Data: An Introduction to Data Mining*", data mining is divided into several groups based on the tasks/jobs that can be done (Larose, 2005), namely:

1. Description
   Sometimes researchers and analysts simply want to try to find ways to describe the patterns and trends contained in the data. Descriptions of trend patterns often provide possible explanations for a pattern or trend.
2. Estimate
   Estimation is almost the same as classification, except that the target variable estimates are more towards numeric rather than categorical. The model is built using complete data rows (*records*) that provide the value of the target variable as the predicted value. Furthermore, in the next review, the estimated value of the target variable is made based on the value of the predictive variable.
3. Prediction
   Prediction is almost the same as classification and estimation, except that in predicting the value of the results will be in the future. Some of the methods and techniques used in classification and estimation can also be used (for appropriate circumstances) for prediction.
4. Classification
   In the classification, there is a categorical variable target. For example, income classification can be separated into three categories, namely high income, medium income, and low income.
5. Clustering (*Clusterring*)
   Clustering is a grouping *record*, observe, or pay attention and form a class of objects that have similarities. Cluster is a collection of *records* that have similarities with one another and have dissimilarity *records* in other clusters. In contrast to classification, in clustering there is no target variable.
6. Association
   The task of association in data mining is to find attributes that appear at one time.

Association Rule Mining

Association rule mining is a procedure for finding relationships between *items* in a specified data *set* (Jiawei Han and Micheline Kamber, 2001). Erwin Yulianto, *et al* (2010) said *Association rules* (association rules) or *affinity analysis* (affinity analysis) with regard to the study of "what with what". For example, it can be in the form of a transaction study in a supermarket, for example someone who buys baby milk also buys bath soap. In this case it means baby milk along with bath soap. Because it originally came from the study of customer transaction *databases* to determine the habits of a product purchased with what product, the association rules are also often called *market basket analysis.* Association rules want to provide this information in the form of an "*if-then*" or "if-then" relationship. This rule is calculated from probabilistic data.

Wanto Anjar , et al, (2020), in his book said that an important type of pattern that can be found from databases is a rule. Two important measurements for a rule are support and confidence. We can compute all association rules with the support and confidence thresholds enter the user by post-processing frequent-itemset.

The Association Rule problem can be composed into two sub-problems, namely:

1. Finding all combinations of items, called frequent-itemsets, whose support is greater than the minimum support.
2. Use frequent-itemset to generate the desired rule. The idea is, say, ABCD and AB occur frequently in transactions, then the rule AB CD will be satisfied if the ratio of support

(ABCD) to support t (AB) minimum of minimum confidence . All rules will have a minimum support because ABCD often appears in transactions.

According to Kusrini (2009), the basic methodology of association analysis is divided into two stages:

1. High frequency pattern analysis
   This stage is looking for a combination of items that meet the minimum requirements of support in the database . The support value of an item is obtained by the following formula.

$$\text{Support (A)} = \frac{\text{Total transactions contain A}}{\text{Total transactions}}$$

$$Support\ (A,B) = P\ (\ A\ \cap B\ )$$

$$Support\ (A,B) = \frac{\sum The\ transaction\ contains\ A\ and\ B}{\sum Total\ transaction}$$

   An analyst may only take rules that have high support and/or confidence . Strong rules are rules that exceed the support and/or confidence criteria minimum . For example, an analyst wants a rule that has more than 20% support and more than 35% confidence . An item set is the set of items in I , and k-itemset is an itemset containing k-item . For example {The,Sugar} is a 2-itemset and {The,Sugar,Bread} is a 3-itemset . Frequent Itemset shows the itemset that has a frequency of occurrence more than a predetermined minimum value (Φ) . Suppose Φ= 2 , then all itemsets whose occurrence frequency is more than or equal to 2 times are called frequent. The set of frequent k-itemset is denoted by F_k .
2. Formation of Association Rules After all frequency patterns are found, then search for association rules that meet the minimum requirements for confidence by calculating the confidence of the associative rules A →B . The confidence value of the rule A →B is obtained from the following formula.

$$\text{Confidence} = \text{P(B | A)} = \frac{\sum \text{The transaction contains A and B}}{\sum \text{The transaction contains A}}$$

   There is a transaction D having itemset J = {i1, i2, … , im} . Each transaction has an identity that is TID . For each TID that D , has an itemset T where T ⊆J . A is said to be a transaction D if and only if A ⊆T . Association rule is a form of implication A ⇒B where , A ⊂J , B ⊂J and A ∩B = ∅. A rule A ⇒B has support s, where s is the percentage of transactions in D consisting of A ∪B with probability P(A ∪B) . Rules AB has confidence c , where c is the percentage of transactions in D that include A as well as B .

$$\text{Support } (A \Rightarrow B) = P(A \cup B)$$

$$\text{Confidence } (A \Rightarrow B) = P(B \mid A)$$

Rules that satisfy both the minimum support threshold (min_sup) and the minimum confidence threshold (min_conf) are called strong. With determination, write the value of support and confidence between 0% and 100%. The set of items is called an itemset. An itemset consists of k items is k- itemset. The set { computer, financial_management_software } is a 2-itemset . The itemset meets the minimum support if the frequency of occurrence of the itemset is greater than the product of min_sup and the total number of transactions in D (min_sup* total transactions). The number of transactions required by the itemset to meet the minimum support therefore refers to the minimum support count . If the itemset meets the minimum support , it is called a frequent itemset. A set of frequent k - itemset is denoted by Lk (Jiawei Han and Micheline Kamber, 2001).

Apriori Algorithm

According to Jiawei Han and Micheline Kamber (2001), apriori is the influential algorithm for mining the frequent itemset for the boolean association rule. The name of this algorithm is based on the fact that it uses prior knowledge of the frequent itemset property.

Apriori uses a level-wise search approach, where k - itemset is used to explore (k+1) -itemsets. First, the set of frequent 1 - itemsets is found. It is denoted by L1. L1 is used to find L2, the set of frequent 2 - itemsets, which is used to find L2 and so on until no more k- itemsets are found. To find each Lk requires $_{searching}$ the entire database.

"How are a priori properties used in algorithms?" There are two steps which include join and prunes.

1. Join Step: to find L_k, a candidate set k- itemset is created by joining L_{k-1} with L_{k-1}. Set candidate is denoted by C_k. Let L1 and L2 be itemset _ _ L_{k-1}. The notation l_i [j] refers to an item jth in li (eg, L_1 [k-2] points to the last 2 of L_1).
2. Prune Step: C_k is a super set of L_k, its members may or may not be frequent, but all frequent k-itemsets are included in C_k. A scan of the database shows the number of each candidate in C_k resulting in the determination of L_k (for example, all candidates totaling not less than the minimum number of supports are frequent , therefore they belong to L_k)

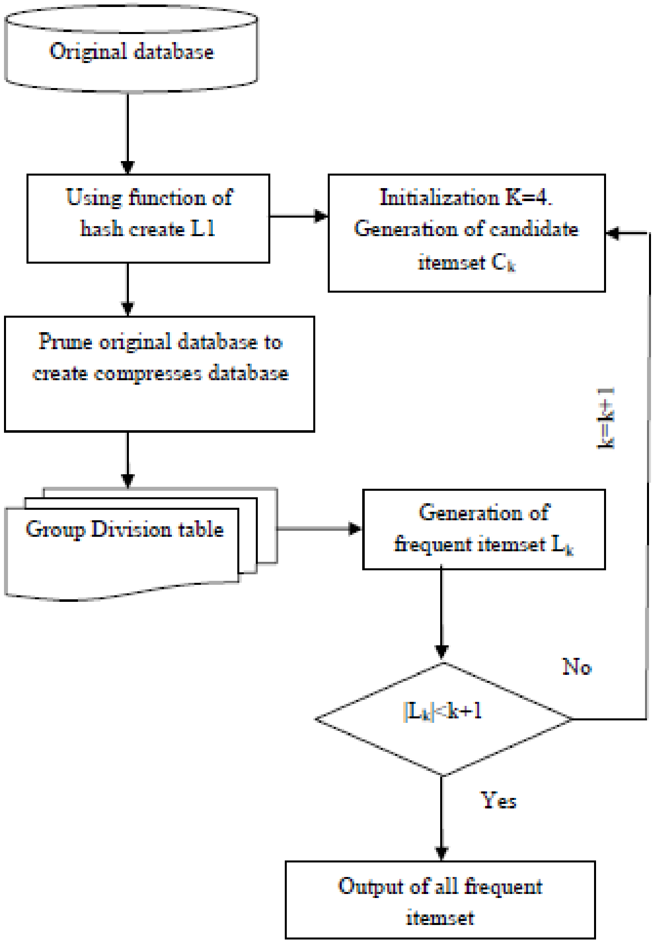

Figure 1: *Apriori* Algorithm *Flowchart*
Source: (D. Magdalene Delighta Angeline and Samuel Peter James, 2012)

Tanagra

Tanagra is software Data Mining is free for academic and research purposes and it proposes several data mining methods from data exploration analysis, statistical learning, machine learning and database areas. Tanagra is an "open source project" because any researcher can access to the source code, and add his own algorithm, as long as he agrees and complies with the software distribution license (Wida Prima Mustika, et al , 2020) . The main goal of the Tanagra project is to provide researchers and students with an easy to use data mining software, conforms to the present norms of software development in this domain (especially in GUI design and ways to use it), and allows to analyze both data real or synthetic. (Najib, et al , 2020).

3. Method

The data collection method used is a questionnaire using a google form which is distributed via whatsapp messages to each respondent. To determine the number of samples from this study the researcher using the Slovin formula because the population in this study is known for certain. The formula used is as follows:

$$n = \frac{N}{1+Ne^2}$$

Information:
n = sample size
N = population size
e = tolerance accuracy % (this study uses a tolerance of 5%).

$$n = \frac{130}{1+(160\ (0,05)^2}$$

$$n = \frac{130}{1,325}$$

$n = 98{,}11$(rounded to 98)

The sample used in this study was 100 respondents. The following is a list of the statements submitted:

Work Engagement

1. When I wake up in the morning, I feel happy to go to work
2. I feel very excited at work
3. I can work for a very long time
4. At work I am always diligent and persistent to do my job
5. I am proud of my current job as a lecturer, because it can be useful for others
6. I teach with all my heart until students are comfortable in my class and easy to understand
7. I am very enthusiastic (passionate) with my work as a lecturer
8. It is very difficult for me to be able to disengage from my work
9. I focus when I'm at work and feel time flies
10. I feel happy when I work really hard

Work Life Balance

1. I can still do the activities I want at home even though I'm tired after work
2. My current job does not place a significant burden on my daily life.
3. I can do activities that I like (hobbies) even though I am working
4. I can still work well even though there are problems at home.
5. I will work overtime even though there are many activities at home
6. I still feel comfortable at work even though there are many problems at home
7. Working as a lecturer gives enthusiasm to do many activities.
8. When my child or family member is sick, I am not confused about taking care of him
9. The atmosphere at home makes me feel good at work.
10. The atmosphere at home makes me happier and ready to work

Then each statement is assessed using five scales, namely:

1. Strongly agree
2. Agree
3. Hesitating
4. Disagree
5. Strongly Disagree

For the dependent variable, namely lecturer performance, the data is obtained from the 2020 lecturer performance index list from the Unilak Quality Assurance Agency.

The next step is data pre-processing: Data pre-processing is one of the most important steps in a data mining process which deals with the preparation and initial transformation of datasets. Preprocessing data describes the types of processes that perform raw data to prepare the process more easily and effectively for user requirements. After that, proceed to the data cleaning stage from the data that has been obtained, cleaning the data from duplication is carried out on survey data and removing attributes or data that are not used in a classification process. In the data cleaning process, there is data mining processing where variables that are not important will not be used. Then proceed to the stage of the mining process using association rule mining.

4. Result and Discussion

Pre Process

This pre-process stage includes data cleaning, data integration, task relevant data, namely selecting data that has relevant attributes. The cleaning method is to remove unused attributes and ignore incomplete data. Task relevant data is to select data that has relevant variables. The variables used consist of:

a. Work Engagement
b. Work Life Balance
c. Lecturer Performance Index

The attributes of the above variables used are:

a. Lecturer's name as a liaison to the questionnaire whose initials were changed in the process.
b. Statement of work engagement questionnaire as an indicator of research objectives
c. The statement of the work life balance questionnaire as an indicator of the essence of the research objectives
d. The value scale of each standard is an attribute associated with a questionnaire statement and the level of performance of the lecturer.

The next stage is data integration. Data integration is the process of converting or merging data into an appropriate format for processing in association rule mining. At this stage do simplification of the value of each attribute is done by providing a code label. Such as the attribute statement "When I wake up in the morning, I feel happy to go to work" which is simplified with the code label "A4" and the attribute scale value statement "4" becomes a value with a simplified format of "agree". This process is done to make it easier processing on data.

In this study, the value of support and confidence will be sought from the combination of the attribute type of ability with the attribute of the type of ability parameter. The dataset is processed with the help of the Tanagra application. The statement attribute is replaced with the letters A to T, the number represents the statement value scale and Y for the lecturer's performance index value. The dataset used consists of 100 transaction data.

Inisial	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	Y
WA	A5	B3	C5	D5	E5	F3	G5	H5	I5	J5	K2	L3	M3	N5	O3	P4	Q5	R1	S3	T3	Y4
IB	A4	B4	C4	D4	E5	F5	G5	H4	I4	J4	K4	L4	M4	N4	O2	P4	Q4	R4	S4	T4	Y4
NN	A4	B5	C5	D5	E5	F4	G5	H4	I5	J5	K5	L5	M4	N4	O5	P4	Q4	R4	S4	T4	Y4
RP	A4	B4	C4	D5	E5	F5	G4	H4	I5	J4	K4	L4	M4	N4	O2	P4	Q5	R4	S4	T4	Y4
WA	A5	B3	C5	D5	E5	F3	G5	H5	I5	J5	K2	L3	M3	N5	O3	P4	Q5	R1	S3	T3	Y4
IB	A4	B4	C4	D4	E5	F5	G5	H4	I4	J4	K4	L4	M4	N4	O2	P4	Q4	R4	S4	T4	Y4
IF	A4	B5	C5	D5	E5	F5	G4	H4	I3	J4	K5	L5	M5	N4	O4	P4	Q4	R4	S4	T4	Y4
ST	A5	B4	C2	D4	E5	F4	G4	H4	I4	J5	K5	L5	M4	N5	O2	P2	Q4	R5	S2	T2	Y4
IB	A4	B4	C4	D4	E5	F5	G5	H4	I4	J4	K4	L4	M4	N4	O2	P4	Q4	R4	S4	T4	Y4
ST	A5	B4	C2	D4	E5	F4	G4	H4	I4	J5	K5	L5	M4	N5	O2	P2	Q4	R5	S2	T2	Y4
IA	A5	B5	C4	D4	E5	F5	G5	H4	I4	J5	K4	L4	M4	N4	O4	P4	Q4	R4	S4	T4	Y4
WA	A5	B3	C5	D5	E5	F3	G5	H5	I5	J5	K2	L3	M3	N5	O3	P4	Q5	R1	S3	T3	Y4
IF	A4	B5	C5	D5	E5	F5	G4	H4	I3	J4	K5	L5	M5	N4	O4	P4	Q4	R4	S4	T4	Y4
BT	A4	B4	C4	D5	E5	F5	G4	H4	I5	J4	K4	L4	M4	N4	O2	P4	Q5	R4	S4	T4	Y4
BN	A5	B3	C5	D5	E5	F3	G5	H5	I5	J5	K2	L3	M3	N5	O3	P4	Q5	R1	S3	T3	Y4
BM	A4	B5	C5	D5	E5	F5	G4	H4	I3	J4	K5	L5	M5	N4	O4	P4	Q4	R4	S4	T4	Y4
ER	A4	B4	C4	D4	E5	F5	G5	H4	I4	J4	K4	L4	M4	N4	O2	P4	Q4	R4	S4	T4	Y4
FT	A5	B5	C4	D4	E5	F5	G5	H4	I4	J5	K4	L4	M4	N4	O4	P4	Q4	R4	S4	T4	Y4
NY	A3	B4	C4	D4	E4	F4	G4	H2	I4	J4	K4	L4	M5	N2	O2	P2	Q5	R5	S5	T5	Y4
NJ	A4	B4	C4	D5	E5	F5	G4	H4	I5	J4	K4	L4	M4	N4	O2	P4	Q5	R4	S4	T4	Y4
FW	A4	B3	C3	D4	E5	F5	G4	H5	I5	J5	K3	L2	M2	N2	O3	P3	Q3	R3	S4	T4	Y4
SW	A2	B2	C5	D4	E4	F4	G4	H4	I5	J4	K3	L2	M2	N2	O1	P2	Q4	R4	S4	T4	Y4
SD	A4	B4	C4	D4	E5	F4	G4	H4	I4	J4	K4	L4	M4	N2	O4	P2	Q5	R5	S5	T5	Y4
SY	A3	B3	C2	D4	E4	F3	G3	H2	I4	J4	K4	L4	M4	N4	O2	P2	Q4	R3	S4	T4	Y4
SO	A5	B5	C4	D4	E5	F4	G5	H4	I5	J5	K4	L5	M5	N4	O4	P4	Q4	R5	S5	T5	Y4
SH	A4	B5	C4	D5	E5	F5	G5	H4	I5	J4	K4	L3	M3	N4	O4	P3	Q4	R4	S4	T4	Y4
LL	A4	B5	C4	D5	E5	F5	G5	H5	I5	J5	K5	L5	M5	N5	O3	P4	Q5	R5	S4	T4	Y4
IA	A5	B5	C4	D4	E5	F5	G5	H4	I4	J5	K4	L4	M4	N4	O4	P4	Q4	R4	S4	T4	Y4
NN	A4	B5	C5	D5	E5	F4	G5	H4	I5	J5	K5	L5	M4	N4	O5	P4	Q4	R4	S4	T4	Y4

Figure 2: Dataset

Association Rule Mining Process

This stage is the data mining stage, which at this stage will be discussed application of association rules with a priori algorithms to find the relationship pattern of work engagement and work life balance patterns on the performance of female lecturers.

Starting association rule mining with an a priori algorithm, first determine the minimum support and minimum confidence. Researchers determine the minimum support is 55% and the minimum confidence is 95%. After that find all combinations of items. The author analyzes with the Tanagra application. Association rule mining in Tanagra can be formed with predetermined steps. This step consists of:

1. Determination of Support and confidence

   Determination of Support can be seen in the algorithm below which consists of input, output and process. Here are the results of the analysis that the author did.

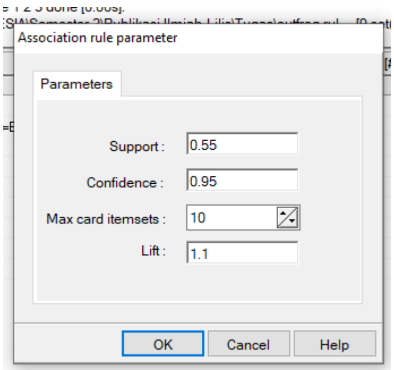

Figure 3: Support and Confidence

   Then get to the point of the association rule problem which is consists of two processes:

2. Find frequent itemsets , i.e. itemsets that have support greater than minimum support .

ITEMSETS [#9 itemsets loaded]

N°	Description	Support
1	M=M4 /\ E=E5	56.0
2	N=N4 /\ H=H4 /\ E=E5	56.0
3	N=N4 /\ H=H4	56.0
4	N=N4 /\ E=E5	57.0
5	J=J5 /\ E=E5	57.0
6	P=P4 /\ E=E5	63.0
7	F=F5 /\ E=E5	64.0
8	Y=Y4 /\ E=E5	63.0
9	H=H4 /\ E=E5	73.0

Figure 4: Itemset which is frequent itemset

3. Uses frequent itemset to generate association rules.
4. Itemset which is frequent itemset hereinafter referred to as rule . From these rules , look for a rule which is an association rule or an associative rule because it meets the minimum confidence requirements .

ITEMS

Transactions	100
Counting items	
All items	129
Filtered items	8
Counting itemsets	
card(itemset) = 2	11
card(itemset) = 3	3
Rules	
Number of rules	10

RULES

Number of rules : 10

N°	Antecedent	Consequent	Lift	Support (%)	Confidence (%)
1	"E=E5" - "N=N4"	"H=H4"	1.32764	56.000	98.246
2	"E=E5" - "M=M4"	"H=H4"	1.32722	55.000	98.214
3	"N=N4"	"E=E5" - "H=H4"	1.32263	56.000	96.552
4	"M=M4"	"E=E5" - "H=H4"	1.32180	55.000	96.491
5	"N=N4"	"H=H4"	1.30475	56.000	96.552
6	"M=M4"	"H=H4"	1.30394	55.000	96.491
7	"P=P4"	"E=E5"	1.11111	63.000	100.000
8	"H=H4" - "F=F5"	"E=E5"	1.11111	55.000	100.000
9	"H=H4" - "N=N4"	"E=E5"	1.11111	56.000	100.000
10	"H=H4" - "M=M4"	"E=E5"	1.11111	55.000	100.000

Figure 5: Association Rule

There are 10 association rules generated. One of the resulting association rules is E5, N4 →H4 With a support value of 56% and 98% confidence. The rule can be translated that 35.29% of the analyzed data shows that female lecturers who are in the dedication aspect of work engagement state strongly agree that they are proud of their work as lecturers, and agree that it is very difficult to get away from their work, and in work life balance, they agree that they can still be work well even though there are problems at home, simultaneously have an effect on achieving a very satisfying lecturer performance index. Meanwhile , 98% confidence states the level of trust or confidence, meaning that if female lecturers in the dedication aspect of female lecturers work strongly agree that they are proud of their work as lecturers, and agree that it is very difficult to break away from their work, and in work life balance, they agree. can still work well even though there are problems at home, there is a 98% chance that this aspect will affect the achievement of the lecturer's performance index.

5. Conclusions

After the *association rule mining process* is run by providing a *support value* of 55% and a confidence of 95%, then the rules that meet the requirements are 10 rules. Rules are knowledge generated from association rule mining. This knowledge explains pattern of relationship between *work engagement* and *work life balance* with the lecturer performance index as what is often stated as often very supportive of a satisfactory lecturer performance index .

Acknowledgements
This knowledge can be used as consideration for female universities and lecturers in formulating problem solving for performance management of female lecturers. This knowledge can also be used as a study to develop the use of association rule mining methods.

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