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# Prediction Model of Health Insurance Membership for Informal Workers

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**ABSTRACT *:***
**Background**: Health insurance for informal workers is very important to be managed properly by Indonesian government, especially by Health BPJS. Whereas informal workers mostly belong to the category of near-poor people. The current health insurance scheme will depend on personal insurance or assistance from families and surrounding communities. The ability of informal workers is still in dire need of health insurance assistance. This model of assistance can be formulated through certain schemes based on each group's ability limitations. The purpose of this study is to model predictions of the ability to provide safekeeping funds for health insurance, especially for informal workers in Bogor, through a Data Mining approach. The data used are primary data from a survey of 100 respondents of informal workers in Bogor. The algorithm used to this prediction model is the J48 algorithm. **Conclussion:**The accuracy of the prediction model for the provision of safekeeping funds is 100% with RMSE values 0.2493 and MEA 0.1243. The accuracy of the prediction model for health facilities selection shows a value of 87%.

***KEYWORDS:****Data Mining, Prediction, Health Insurance Membership, Informal Workers, J48 Algorithm*

## I. INTRODUCTION

The Indonesian government continues to work to expand the coverage of health insurance for its people. In order for health insurance to be able to guarantee the entire population without exception, the population groups that exist in the community need to be identified and at the same time can be distinguished characteristics. For this matter, a more specific definition of society is needed. One specification of community groups that approach poor groups is the people who work in the informal sector. The informal workers community is currently more likely to rely on health insurance through personal insurance or expect assistance from the immediate family [1]. As a result there is uncertainty about the availability of health funds and this is often ignored by the informal workers community [2], not a few of whom are informal workers who experience poverty due to illness [3; 4].

The results of the study [2] show that only 73% of the informal sector workers in Indonesia are preparing funds for treatment. Around 41.8% of the informal sector workforce is only able to provide funds between IDR100,000.00 - IDR500,000.00 annually for treatment. The community group is expected to bear a heavy burden if they have to pay for their own health insurance to BPJS Kesehatan. This condition also shows that the ability of informal workers still needs assistance in the form of health insurance, which can be formulated through certain schemes based on the boundaries of each region [5; 6].

The model or formulation of population participation in the informal sector in this program needs to be built, because this population group is very diverse and needs more detailed definitions [7]. Descriptions of the characteristics of informal workers related to willingness and ability to provide health funds can be assessed through simulation and data mining approaches. The study [2] shows that the primary data surveyed by the informal workers community can be used to predict the ability to participate in the BPJS or predict facilities commonly used by informal workers for treatment. Thus this model can be used by stakeholders for policy formulation and development of other BPJS schemes related to services to the informal worker community [8; 9; 10].

In some studies, predictive model simulations can be built using a computational approach through the data mining process. Data mining is able to provide more specific meaning even unexpected. This is achieved through the process of extracting knowledge using a learning machine. Machine learners can process large data that includes interdisciplinary subjects, and are able to cut process time with maximum accuracy [11]. Data mining has also been tested on relatively small data for cases of student graduation prediction. The attribute pattern used has similarities with the attribute pattern for the case of this study. The results of the study [12] showed that the student graduation prediction model built using three learning machine techniques (M5P, REPTree and J48), was able to be implemented with a high level of accuracy up to more than 95%. The data used consists of 106 records and 13 attributes, with a total of 74 training data lines and 32 test data lines.

The use of data mining for the substance of health insurance or related fields has been carried out [13] to identify the user acceptance model of the health referral system using the ordinal logistic regression. Research [14] has also used the concept of data mining to make a selection model for health-guidance candidates that can reduce referral costs. Implementation of the 5 big data analytic concepts has been tested in the case of healthcare organizations. The concept is proven to have good capabilities for pattern of care, unstructured data capability, decision support capability, predictive capability and tracebility [15]. In this study the concept of data mining is used to predict the participation of BPJS for informal workers and identify health facilities that are more in demand by informal workers. The data mining model used is the classification model, which was tested using two learning machines, namely the J48 algorithm. The selection of the J48 algorithm, known as the C45 algorithm for this study, is supported by several studies that show the performance of the J48 algorithm is superior compared to other algorithms in its class. This refers to the pattern of data used having similarities with the data used in this study, although it does have differences in the case area [16; 17; 18; 19].

The purpose of this study is to build a prediction model for BPJS participation and the use of health facilities by informal workers based on several criteria including status, number of living dependents, education, savings, movable asset ownership, bpjs, reasons for not having BPJS, and willingness to guard funds. The target class used in making this prediction model is the participation of BPJS and health facilities commonly used by informal workers. This research is expected to be able to help the government, especially social services and health offices and related agencies in determining service improvement policies and efforts to increase participation for informal workers who still show a low level of participation.

## II. BASIC CONCEPTS

Efforts to improve health insurance at Municipalities are carried out by integrating cross-sectoral policies. The Healthy City Movement as one of the popular policies can be implemented in people's lives. The emergence of a new paradigm that health as an important factor in people's lives, is the key to the success of the health insurance program [4]. In Indonesia, the implementation of health BPJS has succeeded in raising the poor to almost poor. Health facilities chosen by them are outpatient in private hospitals / doctors / clinics [20]. Health insurance for the informal sector community in Cambodia is reviewed through policy documents using unstructured questions, involving government, non-government and related officials. Data analysis uses the organization's assessment factors to build a framework for improving and strengthening health financing. The results of the study indicate that appropriate institutional and organizational arrangements are able to provide effective health protection for the informal sector in developing countries [3].

Stakeholders including the government, BPJS, ulama, and the supervisory board work together to optimize health insurance in Indonesia [21]. In line with that in Europe, the design of health financing system policies based on decision makers involving stakeholders from the Ministry of Health, Health Insurance Funds and Professional Associations [9] was drafted. Cases of failure of health insurance in Lithuania, Ukraine and Poland are indicated by the high availability of health infrastructure. This triggered an increase in corruption, bribery and informal payments for increasingly uncontrolled health services [22]. Regarding health insurance for non-formal industries in Indonesia has been rolled out but still needs improvement and a tighter control system [10]. Strengthening social security that is very influential on the health insurance of informal workers is through reforming the bureaucracy and fostering small micro-enterprises [22]. Other important factors are improving education, information access and the economy [23]

Small micro business actors are closely related to informal workers. The process of identifying the characteristics of the informal sector community in Indonesia is carried out by [7]. There are at least seven characters that distinguish between the formal and informal sectors [24], namely ease of entry, ease of obtaining raw materials, ownership, scale of activities, use of labor and technology, demands on expertise, and deregulation and market competition. The results of the study [25] show that the informal economy is part of a market economy that has no rules / informal [26], low requirements, operate on a small scale, skills are obtained from outside formal schools and production technology is "labor intensive". Meanwhile [27] adds that the informal economy is a business unit involved in the production of goods and services with the main objective of creating employment opportunities and income for the people involved. Labor relations are mostly based on precarious work, brotherhood or personal and social relationships.

The need for fast and accurate data access to handle health insurance problems, resulting in an increase in the utilization of information technology that is quite effective in its management [1; 13; 28]. Online data access is needed for the development of health service organizations, including health insurance organizations established in each country [4; 28]. Transforming online access is one effective way of patient co-creating value activities [29; 30]. The results show that pre-encounter information activities have a positive impact on developing service service commitments and medical instructions. Increasingly increasing online access causes the need for information security to increase [31; 32]. The culture of seeking and sharing health information through social media has also become one of the phenomena that influences the development of health organization management strategies [31; 29]. The intensity of seeking and sharing of health information is even a very interesting finding because it has involved non-healthcare professionals in its development [31]. The Framework Information Security Management (ISM) implemented in health facilities is very interesting to study, because it is related to a set of strategies that must be prepared by stakeholders [33; 15; 6].

This research aims to build a predictive model of the potential participation of BPJS for informal workers. Prediction models can be implemented using a classification approach. The classification process is one of the data mining techniques that is influenced by the behavior and attributes of groups that have been previously defined [11]. This model provides a classification of new data by manipulating existing and classified data and using the results to provide a number of rules. These rules are used on new data to be classified. Classification prediction models use supervised induction, which utilizes a collection of tests from classified records to determine additional classes. One approach that is often used is the Decision Tree. This approach is the most popular because it is easy to interpret. Classification consists of two steps process, namely learning step (classification model is built) and classification step (model used to predict class labels for given data) [11]. General classification can be processed through four approaches namely Probabilistic Classification, Decision Tree Clasifier, Linear Discriminant Analysis, and Support Vector Machines [34].

Determination of organizational strategies in various fields including organizations that manage health facilities [31; 30; 28] and health insurance have utilized the concepts of data mining or big data [13; 14; 10]. The concept of data mining uses a pattern extraction process or interesting knowledge (non-trivial, implicit, previously unknown, and very potential for a variety of uses) from a large-scale database called data mining [11]. Data mining is successful for small-scale data [35; 12], using certain data patterns. This is in accordance with the data pattern of this study. Data mining functions can include characterization, discrimination, association, classification, clustering, trend / deviation, outlier analysis, and others. Data mining is also an area of research that brings together multiple disciplines, including the fields of Machine Learning, Statistics, Database Technology, Pattern Recognition, Data Warehouse, Algorithms, Applications, Visualization and others [11; 34].

## III. METHOD

The research method applied in this study uses the concept of data mining approach [11; 34]. This stage of research is also known as the Knowledge Discovery and Data mining (KDD) stage which includes the collection and use of historical data to find order and determine patterns or relationships in data sets. The concept of data mining to compile a prediction model for BPJS participation and identification of health facilities chosen by informal workers is based on the stages of data mining in the KDD concept. as shown in Figure 1.

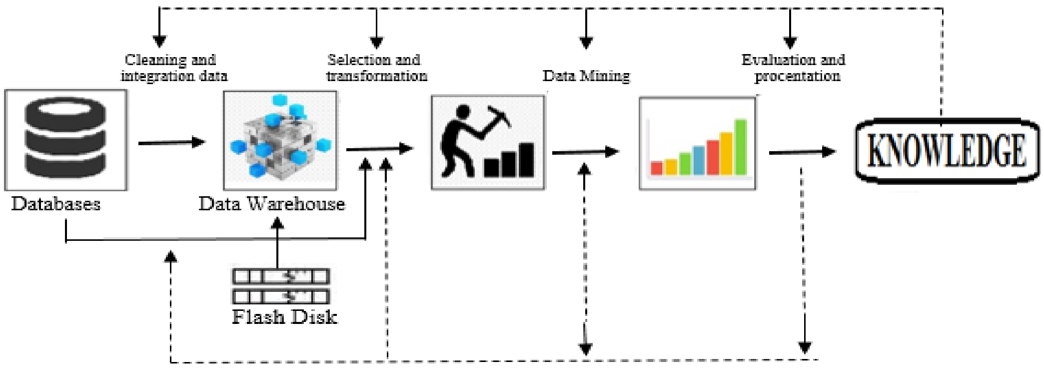


Figure 1. Data Mining Process[11]

3.1 Database Formulation

3.1.1 Description of Preleminary Data

BPJS data was obtained from direct data taken from 100 respondents in the Bogor city area in 2017 [2; 36]. Data consists of 100 lines with the attributes used are 10 attributes. The selection of attributes used is the attribute that has the least missing value. Separating the main attributes from the derived attributes, and reducing the redundant attributes. The results of the dataset involved in the next process have a data structure as shown in Table 1.

Table 1. Data structure predictions of the participation of BPJS for informal workers in Bogor

| No | Attribute | Data Type | Range |
|---|---|---|---|
| 1. | Status | Categorical | "1 = married", "2 = unmarried", "3 = ever married" |
| 2. | number of dependents | Categorical | "1 = 1 person", "2 = 2 people", "3 = 3 people", "4 = more than 3 people", "5 = none" |
| 3. | Education | Categorical | "1 = Never go to school", "2 = elementary school", "3 = junior high school", "4 = senior high school", "5 = other" |
| 4. | Income | Categorical | "1 <= IDR1,000,000.00" "2 = IDR1,000,001.00 – IDR1,500,000.00" "3 = IDR1,500,001.00 – IDR2,000,000.00" "4 >= IDR2,000,000.00" |
| 5. | Saved | Categorical | "1 = none", "2 = any" |
| 6. | Ownership of movable assets | Categorical | "1 = motorcycle", "2 = car", "3 = cart", "4 = none", "5 = pedicab", "6 = no answer", "8 = other" |
| 7. | Has BPJS | Categorical | "1 = None", "2 = Any" |
| 8. | Reason have no BPJS | | "1 = Not had time", "2 = Not thinking", "3 = Trauma", "4 = Have other insurance", "5 = Load", "6 = The process is complicated", '7 = Does not have a KTP "," 8 = Still processed, "" NULL = Has BPJS " |
| 9. | Unexpected needs | Categorical | "1 = <500,000", "2 = 500,001-1,000,000", "NULL = No set aside" |
| 10. | Health facilities | Categorical | "1 = Puskesmas", "2 = Hospital", "3 = Polyclinic / Doctor practice", "4 = other", "NULL = No answer" |

3.1.2 Pre Process Data (Missing Value, Normalization and Discretization)

Data in Table 1. Then processed by filling in the empty cell (missing value). Data with empty cell Categorical type is filled with the value of the mode. The process of forming a prediction model for participation in health insurance for informal workers will be formed by two models. The prediction model for the participation of the health BPJS that was first formed through 9 attributes with the target class is the ownership of guard funds. The second prediction model is formed through 9 attributes with prediction target class places or facilities commonly used for treatment [20; 7].

3.2 Machine Learning Formulation

This prediction model of BPJS participation for informal workers is carried out through the J48 Algorithm. J48 is a better version of the C4.5 algorithm or optimization of C4.5. The output of J48 is a decision tree. A decision tree similar to a tree structure has a root node, an intermediate node and a leaf node. Each node in the tree has decisions and decisions that lead to results. Decision trees divide the input space from one data set into an exclusive area, each region has a label, value or action to describe the data points. How to separate the criteria used to calculate the best attributes is done by dividing the tree, some training data that reaches a certain node. Figure 3 shows the stages of decision tree formation

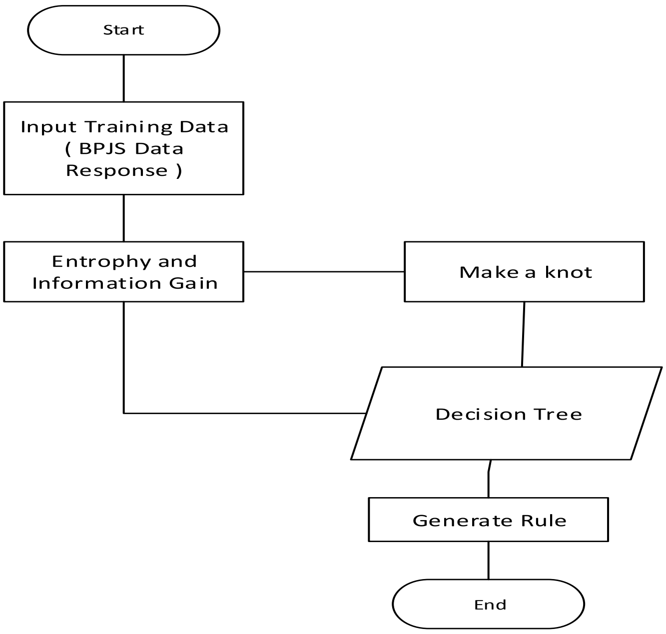


Figure 3. Stages of decision tree formation predict the participation of BPJS health for informal workers

Decision trees are built by dividing data recursively until each section consists of data from the same class. The split form used to divide data depends on the type of attribute used in the split. The C4.5 algorithm forms a decision tree by looking for information gain and entropy values so that this algorithm can form a decision tree rule in predicting health insurance for informal workers [11; 34].

The C4.5 algorithm builds a top down decision tree, starting with the question which attribute must first be checked and placed in the root. This question is answered by evaluating all existing attributes using the statistical measure of the gain ratio to measure the effectiveness of an attribute in classifying a collection of data samples. Classification can be seen as a mapping of a group of sets of attributes from a particular class. In carrying out the separation of objects (split) a test is performed on attributes by measuring the level of impurity of the fruit node (node). C4.5 algorithm uses the gain ratio.

Before calculating the acquisition ratio, it is necessary to first calculate the value of information in units of bits from a collection of objects. The method of calculating is done using the concept of entropy. The general steps of the C4.5 algorithm in building decision trees are as follows:

1) Select attributes as root.
2) Make a branch for each value.
3) Divide cases in branches.
4) Repeat the process for each branch until all cases in the branch have the same class.

To select an attribute as a root node, it is based on the highest Gain value of the existing attributes. To get a Gain, you first need to calculate Entropy. Entropy is a parameter to measure the heterogeneity (diversity) of a collection of data samples. If the collection of data samples is increasingly heterogeneous, the entropy value is greater [34].

Mathematically, entropy is formulated in equation (1). where c is the number of values in the target attribute (number of classification classes). While pi states the number of samples for class i,

$$Entropy\ (S) = \sum_{t}^{c} -P_i log_2 P_i. \qquad (1)$$

After the entropy value is obtained from a collection of data samples, it can be measured the effectiveness of an attribute in classifying data called the gain ratio. Gain ratio is calculated based on split information which is formulated in equation (2).

$$SplitInformation(S,A) = \sum_{i=1}^{c} - \left|\frac{S_i}{S}\right| log_2 \left|\frac{S_i}{S}\right|. \qquad (2)$$

Where S states the sample set of data and Si to Sc states the subset of data samples that are divided based on the number of variation values in attribute A. Furthermore, the gain ratio is formulated according to equation (3).

$$GainRatio(S,A) = \frac{Entropy\ (S) - \sum_{veValue\ (A)} \left|\frac{S_v}{S}\right| Entropy\ S_v}{SplitInfor\ mation}. \qquad (3)$$

Where V represents a possible value for attribute A, Values (A) is a set of possible values for attributes A. Sv is the number of samples for the value of v, and S is the sum of all data samples. Entropy (Sv) is entropy for samples that have a value of v.

## IV. RESULT AND EXPLANATION

The results of modeling the predictions of holding funds and predicting the usual place of treatment are correlated with several important attributes, shown comprehensively in Figures 2 through 9.

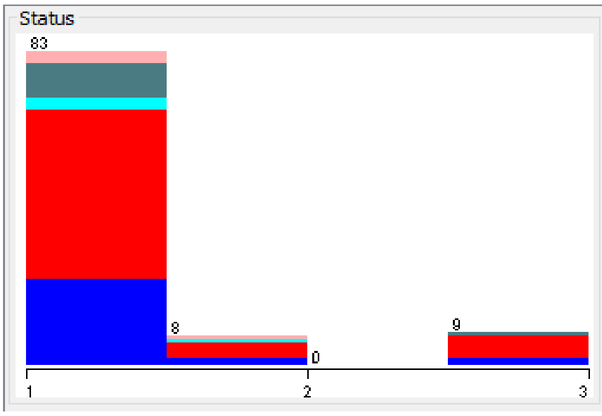


Figure 2. Static condition parameter status

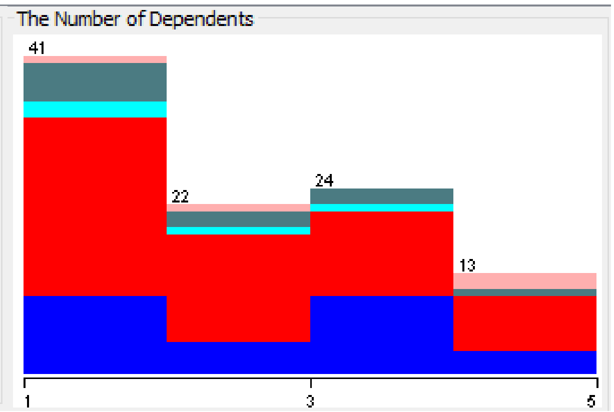


Figure 3. Statistical conditions parameters for the number of dependents 9

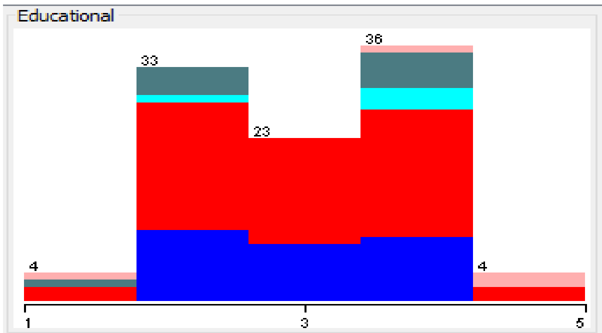


Figure 4. Statistical conditions for educational parameters

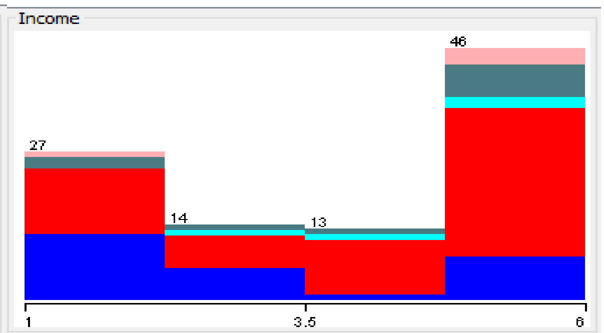


Figure 5. Statistical conditions of income parameters

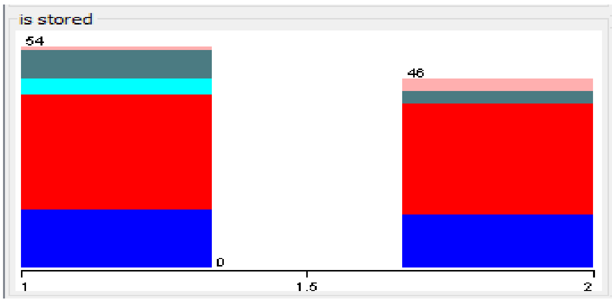


Figure 6. The condition of the statistical parameters is stored

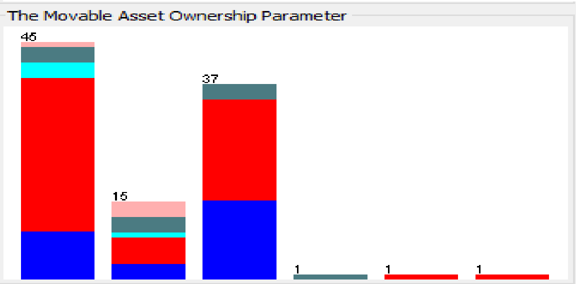


Figure 7. The statistical condition of the movable asset ownership parameter

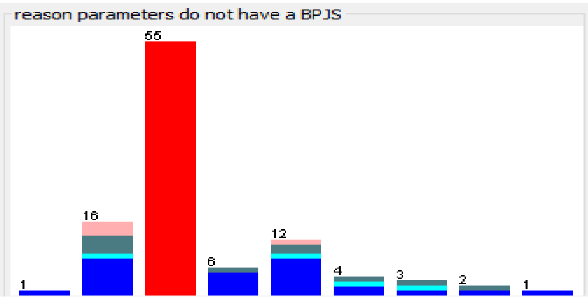


Figure 8. The condition of  parameters have a BPJS

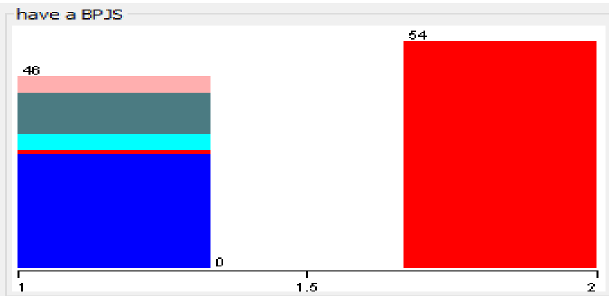


Figure 9. The statistical conditions of the reason parameters do not have a BPJS

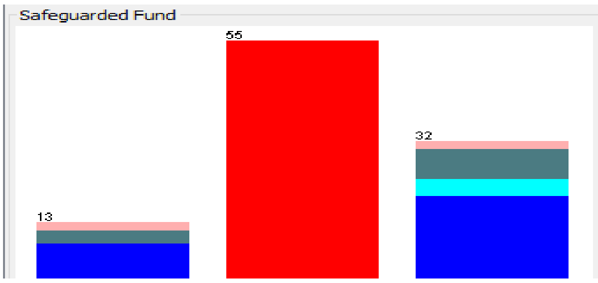


Figure 10. Statistical conditions of safeguarded fund

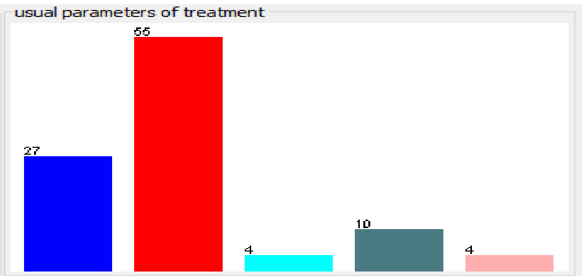


Figure 11. Statistical conditions for usual parameters of treatment

Based on the conditions of the respondents, a prediction process for the holding of funds that can be used for payment of contributions and a strategy for expanding the membership of BPJS membership can be carried out. The prediction process with the J48 algorithm shows good results, as evidenced by the value of accuracy that reaches 100%. Predicted results are shown in Figure 12.

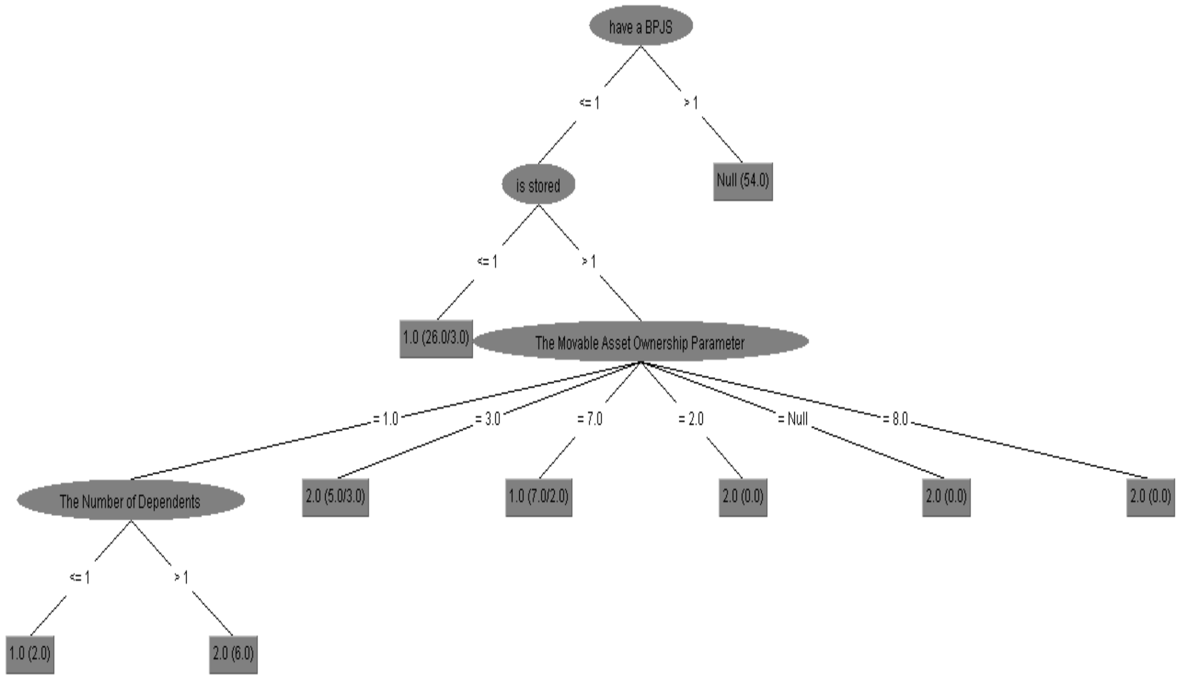


Figure 12. Prediction of Participation in BPJS Health is based on the selection of health facilities

The ownership of savekeeping funds or guard funds for informal workers in Bogor is apparently influenced by the main factors are ownership of the BPJS, ownership of savings, ownership of movable assets and number of dependents. It is very clear that informal workers in the city of Bogor show excellent potential to be directed towards a healthy lifestyle [13; 37], while requiring assistance for good management of household financial management, through saving habits. The number of dependents is the second factor that is very influential on the ownership of funds guarded. This can be a reference for BPJS Health managers to map the conditions of prospective participants, especially from the category of informal workers [1; 2; 8].

The ownership of BPJS for informal workers in the city of Bogor reaches more than 50%, and ownership of guard funds is greatly influenced by the ownership factors of BPJS. Most informal workers choose to have BPJS compared to other insurance [5]. BPJS ownership is considered to have provided high health insurance, so that the ownership of safekeeping funds is neglected if it already has BPJS [2; 36]. Simple lifestyle [37] among informal workers also influences positive behavior to save part of their income. This behavior is indicated by a prediction model that gives a positive figure about the positive correlation between holding funds and saving behavior [13; 4]. Informal workers who do not have the habit of saving are actually predicted not to have guard funds [4]. There is a very interesting thing about the prediction model of safekeeping of funds for informal workers, if seen from the habit of saving and having movable motorbike assets and having dependents, it will be predicted that the funds will be maintained [10; 36]. This pattern can show that informal workers in Bogor have a very good opportunity to be prospected so that they have a stronger health insurance and adequate health financing plan. This can also be examined from the ownership of movable assets in the form of motorcycles. The process of data mining can run well on this data [14; 12] although the data obtained is relatively small [35; 13; 6]. It is evident that a study of strategies for expansion of membership can be carried out [33; 8; 1] by looking at the tendency of prospective BPJS participants from movable asset ownership [14; 6; 36]. Informal workers who have other movable assets such as cars, carts, rickshaws and others are predicted to have guard funds. This can be used as a guide to direct the strategy of expanding BPJS membership [10; 38] referring to the ownership of movable assets [31; 20; 26].

The prediction model for treatment sites commonly used by informal workers is influenced by various factors shown in Figure 13. The accuracy of the model also shows a high value of 87% [14]. This again shows that small data usage is able to provide accurate predictions related to the strategy [9; 14; 39] that can be arranged for the expansion of BPJS participation, especially for informal workers [35; 2; 36].

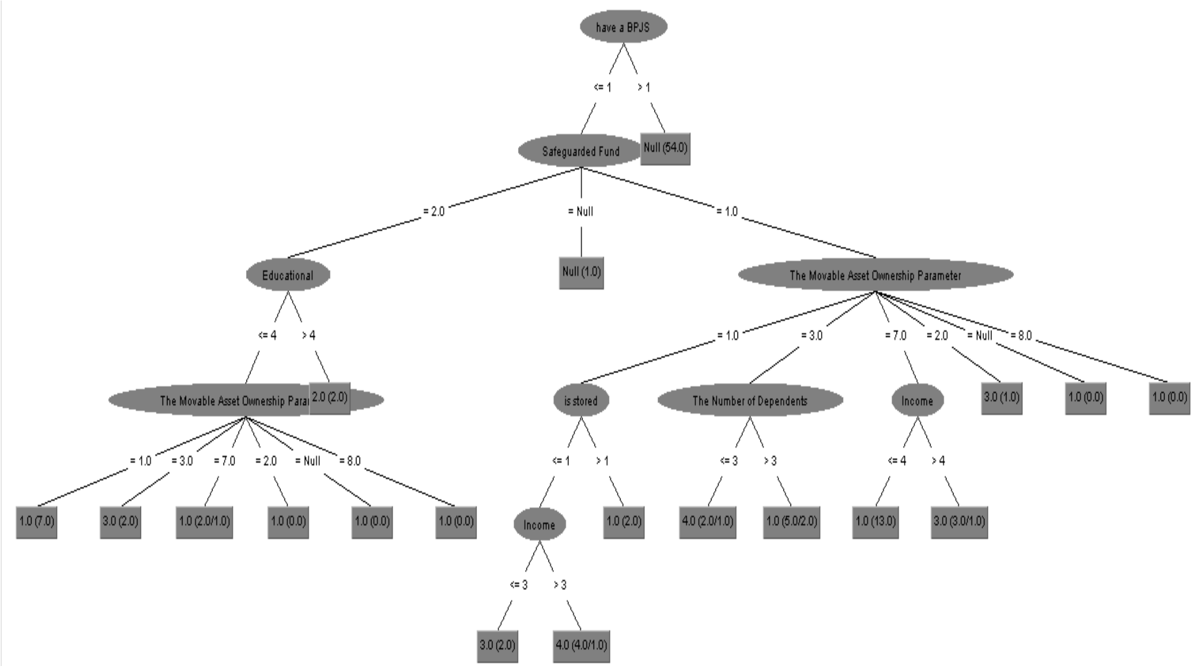

Figure 13. Prediction of healthy behavior patterns of informal workers through the usual conditions of treatment

The prediction model that is formed does have disadvantages due to the lack of systematic instrument compilation. In the prediction model for the selection of medical facilities, informal workers who are already members of the BPJS are no longer mapped in detail. The assumptions used for predicting the selection of treatment facilities for informal workers BPJS participants have followed the Standard Operation Procedure (SOP) [2; 36].

The prediction model for the selection of treatment sites shown in Figure 13 only applies to informal workers who do not have BPJS. The most influential factor is ownership of guard funds. Educational factors have a significant influence on the selection of health facilities commonly used by informal workers in Bogor. Informal workers who have more education than high school will immediately choose the hospital as the main choice of health facilities to be used. Informal workers who have lower secondary education prefer health center health facilities as the main choice. This is in accordance with the study [2; 36; 1] which stated that the Puskesmas was chosen because it was cheap and relatively close to the residence [13; 4; 10].

There are very interesting findings from the prediction model of the selection of health facilities by informal workers in Bogor. Informal workers who have education below high school and have movable assets in the form of carts will prefer polyclinics or medical facilities to practice. Ownership of carts for informal workers is usually owned by mobile sellers, with relatively high income [10] (this is in accordance with Figure 5). Carts are also relatively expensive assets, giving a significant influence on the selection of health facilities [10; 36; 4].

Prediction models are increasingly interesting to study because they show a variety of factors that influence the selection of health facilities by informal workers who are not BPJS participants [5] and do not have guarded funds. The main influential factor is the need to see movable asset ownership. Informal workers who have motorbikes and save money, the choice of health facilities is Puskesmas. Other conditions indicate that lifestyle likes to save very closely with income factors. If the income is less than IDR1,500,000.00 then the choice of health facility is a polyclinic / doctor practice. As for informal workers with the same character but with income of more than IDR1,5000,000.00 they will choose other health facilities. Other health facilities are assumed to be facilities that have higher rental costs [36; 14].

The classification process using the J48 algorithm is also able to specify prediction models. The model is able to show the factors that influence the choice of health facilities commonly used by informal workers rather than BPJS participants and owning carts, apparently influenced by the number of dependents owned. If the number of dependents is owned by more than 3 people, the puskesmas is the most rational choice. Informal workers are not BPJS participants, do not have guard funds and have less than 3 dependents, so they will choose other health facilities that are considered more accessible even though they are relatively more expensive. This condition is very important to be studied, so that BPJS management will be able to develop a new strategy for expansion of membership, especially for informal workers. This very interesting finding can be demonstrated by the data mining process, resulting in a prediction model for the participation of health BPJS with good levels of performance [11; 31; 14].

The ownership of BPJS is again a major factor in determining the pattern of healthy behavior of informal workers in the city of Bogor. This model is able to work very well and the culture of healthy living is formed with the awareness to discipline BPJS Health contributions [21]. Based on Figure 8, it shows that ownership of guard funds is also very important in the participation and sustainability of BPJS Kesehatan. Even the level of education, income and number of dependents are interesting things that can be studied more deeply [1; 36; 4]. One very surprising factor that also influenced the selection of health facilities by informal workers in Bogor was mobile asset ownership [13; 14]. The results of this study are very useful for the formation and tracking of the sustainability strategy and expansion of BPJS membership in accordance with the mandate of the BPJS Law [5; 3].

## V. CONCLUSION

The prediction model of BPJS participation for informal workers can be mapped well through the Data mining process, using the J48 Algorithm, using structured instruments, which are conducted through in-depth interviews with 100 respondents. This study shows that even relatively small data is able to provide accurate prediction models with a high degree of accuracy of 100% for prediction models of safekeeping of funds and 87% for prediction models of health facility selection. This further strengthens the main objective of research to form clear patterns and rules in formulating policies for the sustainability of BPJS Health participation for informal workers. A healthy lifestyle is very much determined by the ownership of guard funds, which ultimately converged on the need to become a BPJS Health participant. Through the J48 algorithm it can be predicted that the ownership of guard funds is strongly influenced by the participation of BPJS Kesehatan. With conditions that are disciplined paying BPJS contributions Health will shape the mindset of healthy living. This is indicated by the influence of the pattern of saving habits that shows a very close relationship to the ownership of funds guarded.

Health BPJS ownership is also a motivation for healthy living with a medical treatment approach. Other factors that greatly influence the pattern of treatment habits are ownership of guard funds, education levels and ownership of movable assets. 30% of informal workers in Bogor show good economic conditions, therefore motivation to live healthy can be predicted from these factors. This study provides a new perception of the Data Mining approach that can work well in small data to predict the conditions and culture of healthy living, through the participation of BPJS.

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**Conflict of Interest**
None declared.

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