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Proposed Assessment Model to Determine the Best Association Mining Technique Related to Business Processes Re-Engineering

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Abstract

Enterprises are human resources that are formed into organizational structures and consume material and financial resources to provide society with service or product. Enterprises are constantly changing to keep pace with the changes that occur in the environment of their services or products. There are several techniques and tools that enable an organization to keep pace with the changes occurring in its environment. One of these techniques is business process re-engineering. Business process re-engineering means making a radical modification in the enterprise's business processes for the enterprise to continue to keep pace with its changing environment. Business process re-engineering is dangerous if it fails. Failure in the task of business processes re-engineering means that the enterprise cannot keep up with the changes and at the same time cannot remain in the state it was in. There are critical success factors in business process re-engineering. Many efforts tried to employ data mining techniques in business processes re-engineering. In this paper, we will propose assessment model to determine the best association mining technique related to business processes re-engineering.

The proposed assessment model contents of five stages as the following: Data preparation related to business process re-engineering, Algorithm selection, Implementation of selected algorithms, Evaluate the performance related to business process re-engineering, Determining the results. The proposed model aims to implement and examine a set of correlation and association algorithms on an available data set related to business process re-engineering and compare the results based on business processes re-engineering performance factors. The proposed model also relied on mathematical analysis of the algorithms chosen to be implemented in this study.

According to that, the methodology using in this study will be based on two stages: The first stage: The methodology of mathematical theoretical analysis for choosing set of algorithms. The second stage: The methodology of experimental implementation and comparison of results based on business processes re-engineering performance standards.

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1. INTRODUCTION

Re-engineering business processes is an interrelated issue that has many considerations. There are several goals of business process re-engineering, for example: increasing productivity [1], achieving high growth, generating competitive advantage, improving services [2], increasing customer satisfaction, reducing costs, and increasing profitability. But all of this may not be achieved in the event of failure to plan and implement the business process reengineering process [3, 4].

Enterprises differ in the dimensions of the composition of their business processes between production Enterprises and service Enterprises. But all enterprises agree that the business process is a carefully studied partial effort that ultimately leads to achieving the organization's general service or production goal [5, 6, 7]. Organizational inflation occurs when business processes become too numerous compared to the need to providing the organization's general service or production goal. This inflation leads to the consumption of human, material and financial resources more than the actual need for them [8, 9]. The critical process in re-engineering business processes is identifying the processes that constitute inflation in the organizational structure, which are considered bureaucratic inflation, and those others that are necessary for the successful provision of the enterprise's service or product to society [10, 11].

In the modern era, enterprises seek to provide their products and services to the society in a more agile and easy way [12, 13]. enterprises are sometimes surprised by the decline in their sales due to the efforts of its competitors [14, 15]. This decrease in sales forces the enterprise to either reduce the price of the product or increase its quality, or both. In all cases, reducing the price of the product or increasing its quality is mainly related to re-engineering business processes to reduce business processes with the aim of reducing costs and at the same time increasing the performance of other remaining business processes [16, 17, 2].

When re-engineering business processes, business processes need examination and study according to deep and important scientific standards. In fact, there are many efforts that have attempted to establish and formulate important standards and factors for business processes. It is mostly centered around the aspects of cost, time, and quality [18, 14]. In this study, we will attempt to present an effort related to using data mining techniques to derive suitable mining technique for business process re-engineering [19, 20, 21]. We will conduct a set of experiments on a data set to choose the best suitable algorithm for use in the case of business process re-engineering. We will use a data set prepared and collected by the Egyptian Tax Authority in accordance with the standards and characteristics related to the business process re-engineering process [22, 23].

There are two types of data mining algorithms: predictive algorithms and descriptive algorithms. Descriptive algorithms are those algorithms that rely on the description of previous historical data in data set, while predictive algorithms are those algorithms that rely on predicting future events based on interpreting and understanding the events in the previous historical data set [14, 24, 25].

In this study, we will use descriptive algorithms of the type of association rules between business process performance standards and critical success factors for business process re-engineering [26, 27]. We need to deeply examine the mathematical formulation of the overall association rule algorithms, determine their efficiency, then project them onto the given data set and extract and display the results.

2. RELATED WORKS

In this part of the research, we will attempt to review previous works related to the assessment and use of data mining techniques in the process of business process re-engineering. Then, we will introduce the weaknesses in the related works. These weaknesses in related works will be the start points to construct our proposed model as the following:

"Towards a Data Science Framework Integrating Process and Data Mining for Organizational Improvement" (2020): In ICSOFT 2020 - 15th International Conference on Software Technologies, Andrea Delgado and others have presented a proposal towards an integrated framework that led to analyse execution data in integrated manner, both from processes and organizational data that are handled by those processes, with a focus on inter-organizational collaborative processes. The proposed framework in this study aims to support and help enterprises in the complete process of analysing their data, from data extraction, data quality evaluation, data format and selection, data integration, application of process and data mining technologies and algorithms, and tool support [28].

"A Methodology for Integrated Process and Data Mining and Analysis towards Evidence-based Process Improvement" (2021): In ICSOFT 2021 - 16th International Conference on Software Technologies, Andrea Delgado and others have presented the PRICED methodology to carry out process and data mining and analysis works over integrated process data and organizational data. The main elements of the proposal of methodology include: integrated process and organizational data, i.e., from process engines and distributed organizational DBs, loaded in an integrated metamodel; quality evaluation over the integrated process and organizational data; extended event logs and a data warehouse to be used for mining analysis over the integrated data; integrated process and data mining analysis methods to introduce complete view of the organization's actual operation. They are applying the proposed methodology over more complex processes to strengthens the capabilities of the approach [29].

"Evaluation of the use of business process re-engineering (BPR) for improving business-IT alignment by utilizing the intelligent decision support system (IDSS)" (2023): In int. J. Nonlinear Anal. Appl. 14 (2023) 1, 505–517 ISSN: 2008-6822 (electronic), Shima Nargesi and Ghassem Ali Bazaee introduced efforts to evaluation of the use of business process reengineering (BPR) for improving business-IT alignment by utilizing the intelligent decision support system (IDSS). An important study results, namely "Designing a neuro-fuzzy decision support system to asses the use of BPR to improve the Business-IT alignment", meant that the status of "improving IT alignment with Tehran-based knowledge-based businesses" could be analysed numerically and mathematically and more accurately according to the rules of knowledge base of the main module of intelligent system based on calculating and determining the weight of each main variable according to the expert's opinions and the intelligent system designed in the study [30].

"Adaptive model to support business process re-engineering" (2021): In PeerJ Comput. Sci., DOI 10.7717/peerj-cs.505 (2021). Noha Ahmed Bayomy et al introduced adaptive model to support business process re-engineering. The proposed model in this study is used to determine where the breakdowns happen in BPR implementation, why they happen and how they can be prevented. This study paves the way for integrating CSFs of BPR and the performance of business processes in order to improve processes and support successful implementation of BPR. According to the results of the study, there are seven identified factors impacting on BPR success (as expressed by measuring performance of business processes) by using data mining techniques includes: (1) organizational structure, (2) use of information technology, (3) adequate financial resources, (4) egalitarian culture and leadership, (5) change management, (6) customer focus and (7) top management commitment. These factors have been integrated with performance of business processes to implement re-engineering the processes of Egyptian Tax Authority successfully through stages of proposed model [22, 23].

"Employing Data and Process Mining Techniques for Redundancy Detection and Analytics in Business Processes" (2023): In international information and engineering technology association (2023). Fatima Zohra Trabelsi and others introduced proposed model to employing data and process mining techniques for redundancy detection and analytics in business processes. In this research, the objective of eliminating redundant processes in business processes is to simplify them and make them more efficient. Redundant processes are steps or activities that are repeated unnecessarily or are not necessary for completing a given task. These processes can cause delays, errors, and additional costs. By eliminating redundant processes, businesses can enhance their productivity, quality, and responsiveness to their customer's demands [31].

"A Literature Review on Business Process Management" (2022): In American Academic Scientific Research Journal for Engineering, Technology, and Sciences (2022). Fatimazohra Trabelsi and others introduced A Literature Review on Business Process Management. They proved that Business Process Management (BPM) has gained high importance in the last decade and is increasingly used in many contexts (marketing, E-Commerce, E-Heath, E-Learning, E-Government). Especially, it is important to efficiently manage these processes vital for the organizational performance in order to continually improve, therefore increasing productivity and competitiveness within the enterprise, and data mining is playing a more important role in developing and enhancing BPM nowadays. The proposed literature review reveals that both BPM and data mining are the primary domains of this study. As a result of searching studies in four digital libraries, they identified at the beginning 3079 papers. Based on many of exclusion criteria and quality evaluation criteria, 51 relevant papers were selected. The reason they used the four electronic libraries because they have the biggest repository for academic study and most widely used by researchers [32].

"A Literature Review for Contributing Mining Approaches for Business Process Re-engineering" (2020): In Future Computing and Informatics Journal, (2020). Noah Ahmed Bayomy and others introduced A Literature Review for Contributing Mining Approaches for Business Process Re-engineering. This paper introduced a discussion of the last researches in the business process re-engineering. The research identifies the breakdowns that are highlighted in different last BPR models, why they happen and how they can be prevented. The research has attempted to discuss the proposed models for BPR in many industries which highlighted that it lacks some development and enhancement. According to the presented discussion, this research paves the way for the opportunity of embedding data mining techniques to raise the performance of business processes in order to improve processes and support successful implementation of BPR [33]. "Evaluating The Performance of Association Rule Mining Algorithms" (2011): K.Vanitha, R.Santhi, in Journal of Global Research in Computer Science. (2011) introduced research about the assessment of association rule mining algorithms. They confirmed that the association rules play a main role in many data mining applications, trying to find interesting patterns in data bases. To obtain these association rules, the frequent sets must be previously generated. The most common algorithms which are used for this type of actions are the Apriori and FP-Growth [34].

"Evaluating the Performance of Association Rule Mining Algorithms" (2017): M. Sinthuja, N. Puviarasan and P. Aruna. In World Applied Sciences Journal 2017 introduced research, a detailed comparison has been made for the frequent pattern mining algorithms of Apriori, ECLAT and FP- Growth. The comparison studies were undertaken with different standard datasets like the mushroom, spect, primary tumor. The resulting analysis shows that the algorithm runtime and memory differ for different datasets [35].

2.1. Weaknesses in related works

It is noted that the related works mentioned previously share the following weaknesses:

2.1.1 The performance goals of business process reengineering vary from one organization to another. Perhaps they may intersect in major common goals. Therefore, we need an evaluation model that identifies appropriate mining techniques considering the performance goals of business process reengineering.

2.1.2 previous works lacked a mathematical analysis of the body of algorithms that are candidates for use in re-engineering business processes in enterprises.

2.1.3 We need an evaluation model, not for the technical evaluation of the algorithm, but rather to test and examine the best algorithms that are suitable for use in re-engineering of enterprises in terms of the comprehensiveness of the association generated, and the ease of understanding and interpreting them

So that, we will develop effective approach include summaries of key studies limitations or finding. According to that, we will develop the new model. We can abstract the important criteria of assessment mining algorithms related to business process re-engineering as the following table 1:

- **D**ata **S**et **R**elated to **B**usiness **P**rocess **R**e-engineering: **DSBPR**
- **Int**erpretability: **INT**
- **Inn**ovation: **INN**
- **R**elated to **B**usiness**P**rocess **R**e-engineering model: **RBPR**
- **E**valuated **A**lgorithm related to **B**usiness **P**rocesses: **EABP**

Table 1. Comparison BPR criteria in previous models

Reference NO	DSBPR	INT	INN	RBPR	EABP
[28]	✓	✓	✓	✓	✓
[29]		✓	✓	✓	
[30]		✓	✓	✓	
[22]	✓	✓	✓	✓	
[31]	✓			✓	
[32]					
[33]		✓	✓	✓	
[34]		✓	✓		
[35]		✓	✓		
PAM	✓	✓	✓	✓	✓

Based on the table above, which briefly summarizes the lack of some previous models in some standards related to business process re-engineering. Whereas some of these standards are presence in other models, the need arises to develop a proposed and improved comprehensive assessment model that takes into account all the standards listed in the table above that are related to the issue of business process re-engineering.

The methodology using in this study will be based on two stages: The first stage: The methodology of mathematical theoretical analysis for choosing set of algorithms. The second stage: The methodology of experimental implementation and comparison of results based on business processes re-engineering performance standards.

3. PROPOSED ASSESSMENT MODEL TO DETERMINE THE BEST DATA MINING TECHNIQUE RELATED TO BUSINESS PROCESSES RE-ENGINEERING.

To assess the best association rules algorithm for business process re-engineering analysis, we can follow the structured proposed assessment model shown in figure 1:

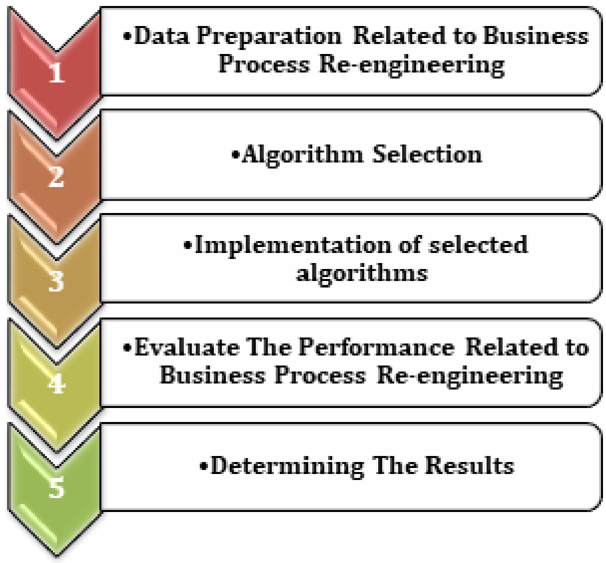

Figure 1. Proposed assessment model to determine the best association mining algorithm related to business processes re-engineering. Adapted from [34, 35]

3.1. Data Preparation Related to Business Processes Re-engineering:

3.1.1 Collect Data: we will gather data relevant to business process. In this regard, we need data that includes the previous goals of business process engineering. There is data set prepared in the Egyptian Tax Authority. This data was prepared specifically for the business process re-engineering model. It includes the previous goals of business process re-engineering. And the dataset was published in international journal of Q1 [22]

3.1.2 Pre-process Data: We should make cleaning and formatting of the data for analysis. However, the previously mentioned data set was clean, free of any outliers, and did not contain any missing values.

3.2. Algorithm Selection:

3.2.1 *Determine the mining pattern and algorithms:* In this sub-stage, we will select the pattern of association rules from data mining patterns. The structure of business process engineering in enterprises depends on the interconnection of business processes with each other to achieve a goal. Therefore, patterns of association rules with classification in data mining are most appropriate for use in the context of business process re-engineering models. We will identify the basic algorithms in the association rules pattern and make mathematical and experimental analysis to determine the best algorithm to use with business process re-engineering models. The main algorithms in the association rules pattern are: *(Apriori, FP-Growth, Eclat and AIS)* algorithms. These algorithms are the basic ones in association rules and most other association algorithms are based on them. Most proposed association algorithms are an adaptive improvement of these main algorithms for the purpose of adapting use in a scientific field.

3.2.2 *Make mathematical analysis of main association rules algorithms:*
In this sub-stage, we will subject the four basic algorithms to mathematical analysis. After that, the algorithms that will pass the mathematical analysis will be subjected to experimental testing.
Association rules algorithms are a set of details used to analyses diamond-sensitive relationships between elements in data sets. These algorithms are particularly useful in purchasing analysis, as they can help identify commonalities between items that can be ascertained. This matter completely intersects with the purpose of re-engineering business processes in enterprises. So, we will make mathematical analysis of some outstanding main selected association algorithms as the following:

3.2.2.1 *Apriori algorithm mathematical analysis:*
One month of algorithms in this field.
Depends on which subgroup cannot be part of a group.
They are used to define basic sets and association rules.
The mathematical analysis as the following:
Apriori Algorithm Steps:

A. Generate Candidate Itemsets:

- Start with 1-itemsets (single items).
- For k-itemsets, candidates C_k are generated by joining L_{k-1} (frequent $(K-1)$ – itemsets) with itself.
- join step

$$C_k = \{A, B \in L_{K-1} | A \cap B| = K - 2\}$$

B. Prune Candidate Itemsets:

Eliminate candidates that have infrequent subsets.
Prune Step: If any subset of candidate c is not in L_{K-1}, remove c from C_K

C. Calculate Support:

- Count the occurrences of each candidate in C_k to determine if it is frequent.
- Support Calculation:

$$\text{Support}(C) = \frac{\text{Number of transactions containing C}}{\text{Total number of transactions}}$$

D. Select Frequent Itemsets:

- Select candidates from C_k that meet the minimum support threshold.
- Selection:

$$L_K = \{C \in C_K | \text{Support}(c) \geqslant \text{minimum support}\}$$

E. Generate Association Rules:

- For each frequent itemset L, generate rules $A \to B$ where $A \subset L$ and $B = L \setminus A$.
- Confidence Calculation:

$$Confidence(A \to B) = \frac{support(A \cup B)}{support(A)}$$

- Select rules where confidence is above a minimum threshold.

F. Iterative Process:

- Repeat steps 1-4 for increasing K until no more frequent itemsets are found.
- This process allows Apriori to efficiently discover frequent itemsets and generate association rules from a transaction dataset.

3.2.2.2 *Eclat Algorithm mathematical analysis:*
It is based on the vertical data partitioning approach.
We create association rules by intersections of repeated elements. It is considered faster than Apriori in some cases. Eclat Algorithm Steps: Eclat (Equivalence Class Clustering and bottom-up Lattice Traversal) is a depth-first search algorithm that uses a vertical data format.

A. Vertical Data Format:

- Each item is associated with a list of transaction IDs (TID list) where it appears.

B. Intersect TID Lists:

- For two itemsets A and B, compute the intersection of their TID lists to find the support of the combined itemset $A \cup B$.
- Intersection:

$$T(A \cup B) = T(A) \cap T(B).$$

- Support:

$$Support(A \cup B) = |T(A \cup B)|$$

C. Recursive Depth-First Search:

- Start with single itemsets and recursively combine them.
- Use the intersection step to generate frequent itemsets.

D. Prune Infrequent Itemsets: If Support ($A \cup B$) is less than the minimum support, prune $A \cup B$.

E. Iterative Process:

- Continue the process recursively for every frequent itemset found, generating larger itemsets by intersecting TID lists.
- This method efficiently discovers frequent itemsets using vertical data representation and intersection operations.

3.2.2.3 *FP-Growth Algorithm mathematical analysis:*

It builds a Frequent Pattern Tree (FP-tree) to store sets of frequent items. It does not require frequent data scanning as in Apriori. It is effective in finding association rules without generating many subsets. FP-Growth Algorithm Steps:

A. Construct the FP-Tree:

- Count Item Frequencies: Calculate the support of each item in the dataset.
- Support Calculation:

$$Support(i) = \frac{\text{Number of transactions containing } i}{\text{Total number of transactions}}$$

- Order items:
- Sort items in each transaction by their frequency in descending order.
- Build the FP-Tree:
- Insert transactions into the FP-Tree:
- If a path for the transaction exists, increment the count.
- Otherwise, create a new path.

B. Mine the FP-Tree:

- *Identify Frequent Patterns:*
- For each item i(starting from least frequent), extract its conditional pattern base:
- *Conditional Pattern Base:*
- For item i, find all paths leading to i and record the prefix path and count.
- *Construct Conditional FP-Trees:*
- Build a conditional FP-Tree for each item based on its conditional pattern base.
- *Recursive Mining:*
- Recursively mine the conditional FP Trees to find frequent itemsets:
- *Frequent Itemset Generation:*
- For each item i, combine it with frequent itemsets derived from its conditional FP-Tree.

C. Generate Association Rules:

- *Generate Rules:*
- For each frequent itemset L, generate rules $A \rightarrow B$ where $A \subset L$ and B $= L \setminus A$.
- *Confidence Calculation:*

$$Confidence(A \rightarrow B) = \frac{Support(A \cup B)}{Support(A)} \quad (1)$$

- FP-Growth efficiently finds frequent itemsets by compressing the dataset into a tree structure and using recursive pattern mining, avoiding the need to generate candidate sets explicitly.

3.2.2.4 *AIS Algorithm mathematical analysis:*

- ⋆ One of the first algorithms developed to extract association rules. It scans the data multiple times to generate sets of frequent items. Less efficient compared to Apriori and FP-Growth. The AIS (Agrawal, Imielinski, Swami) algorithm is an early method for mining association rules. It works in a level-wise manner, generating candidate itemsets and checking their support.

A. Initialize:

- Start with a set of frequent 1-itemsets L_1.

B. Generate Candidate Itemsets:

- For each level K, generate candidate itemsets C_K by extending frequent itemsets L_{K-1} with one more item.
- Candidate Generation:

$$C_K = \{A \cup \{i\} | A \in L_{K-1}, i \notin A\}$$

C. Count Support:

- Scan the database to count the support of each candidate in C_K.
- Support Calculation:

$$Support(A) = \frac{\text{Number of transactions containing A}}{\text{Total number of transactions}}$$

D. Prune Infrequent Itemsets:

- Remove itemset from C_K that don't meet the minimum support threshold, resulting in L_K.

E. Iterate:

- Repeat steps $2-4$ for $k+1$ until no new frequent itemsets are found.

F. Generate Association Rules:

- For each frequent itemset L, generate rules $A \rightarrow B$ where $A \subset L$ and $B = L \setminus A$
- *Confidence Calculation:*

$$Confidence(A \rightarrow B) = \frac{Support(A \cup B)}{Support(A)}$$

- The AIS algorithm works by iteratively generating and testing candidate itemsets, pruning those that are infrequent, and then deriving association rules from the frequent itemsets.

3.2.3 *Choose Candidates:* In this sub-stage, we will determine which candidate algorithms best suits the business process analysis needs according to the step of mathematical analysis. Then, the candidate algorithms will put in experimental method in the advanced stages of this assessment model.

So, In this section, we will conclude and make deep mathematical analysis comparison for the four algorithms based on:

1- Time Complexity.
2- Space Complexity.
3- Support Calculation.
4- Pruning Method.
5- Candidate Generation.

Time Complexity:
A. Apriori:

- $O(2^n.n.|D|)$
- It involves generating and testing many candidate itemsets, leading to exponential complexity.

B. FP-Growth:

- $O(|T|.|I|)$
- Uses a tree structure to store transactions, making it faster for large datasets as it avoids candidate generation.

C. Eclat:

- $O(2^n)$
- Uses a depth-first search approach with TID list intersections, which can be efficient but potentially exponential with large itemsets.

D. AIS:

- $O(2^n.n.|D|)$
- Similar to Apriori, with high complexity due to candidate generation.

Space Complexity:
A. Apriori:

- High due to storing large numbers of candidate itemsets.

B. FP-Growth:

- Low because of its compact tree structure that eliminates the need for candidate sets.

C. Eclat:

- Medium, as it uses TID lists which can be large but typically smaller than full candidate sets.

D. AIS:

- High, like Apriori, due to candidate storage.

Support Calculation:
A. Apriori:

- $\sum_{k=1}^{n} |C_k|$
- Requires scanning the database multiple times for candidate supports.

B. FP-Growth:

- Efficient tree traversal allows quick support calculation without scanning the entire database repeatedly

C. Eclat:

- $|A(T) \cap T(B)|$
- Uses intersection of transaction ID lists to calculate support efficiently.

D. AIS:

- $\sum_{k=1}^{n} |C_k|$
- Similar to Apriori, with multiple database scans.

Pruning Method:
A. Apriori:

- Removes infrequent itemsets early to reduce candidate generation.

B. FP-Growth:

- Uses conditional pattern bases to focus only on frequent patterns.

C. Eclat:

- Prunes based on infrequent intersections.

D. AIS:

- Similar to Apriori, pruning infrequent candidates.

Candidate Generation: **A. Apriori:**

- $|CK| = |L_{k-1}|^2$
- Generates candidates by joining frequent (K – 1) – itemsets.

B. FP-Growth:

- No explicit candidate generation; uses a recursive tree-based approach.

C. Eclat:

- No explicit candidate generation; relies on recursive intersection of TID lists.

D. AIS:

- $|CK| = |L_{k-1}|^2$
- Similar to Apriori in generating candidates.

According to the deep mathematical analysis above, we should rule out in theoretical manner the AIS algorithm because it is a natural evolution of the Apriori algorithm. With some differences, of course, as follows:

Apriori:

- *Generate candidates*: Candidate itemsets are generated in stages using the intersection feature, which reduces the number of candidates.
- *Complexity:* More efficient in dealing with big data because the number of candidates is reduced early.
- *Work method:* It depends on scanning the database multiple times.

AIS:

- *Generate candidates:* Candidates are generated while scanning the database, which may result in a larger number of candidates.
- *Complexity*: Less efficient due to the large number of potential candidates.
  Work method: It generates rules during a single pass through the data.

In fact, these simple differences between the two algorithms (AIS, Apriori) do not constitute a critical issue for business process re-engineering models. We need to generate more association rules at the same value of support and confidence. Because the different views of re-engineering business process models. Also, we need to compare association rule algorithms that are completely different in their synthetic structure. Therefore, we decided at this stage to exclude an algorithm of AIS because its structure is like Apriori algorithm.

While in the Eclat algorithm, as is clear in the above mathematical analysis, it relies on intersection in calculating support, while the FB-Growth and Apriori algorithms depending on summations rules in support calculations. This will lead to the emergence of more associations we need in business process re-engineering models. Therefore, at this stage of the mathematical analysis, the Eclat and AIS algorithms were excluded in theoretical manner but we will implement it for conforming. So, the participants with us in the next stage of the assessment model, which depends on the experimental implementation, are all mining selected algorithms for conforming: Apriori, FB-Growth, Eclat and AIS algorithms.

3.3. Implementation of selected algorithms

In this phase of the proposed model, we will put the main correlation algorithms into implementation experiments by using python. We will implement the main association algorithms on the dataset which identified in the first phase of this model. The selected dataset related to business process re-engineering. Then, we subject the implementation results of each algorithm to the performance criteria associated with business process re-engineering.

3.4. Evaluate The Performance Related to Business Process Re-engineering:

In this stage of the assessment model, we will put the implementation results of each algorithm in comparing with the performance factors of business process re-engineering. We will list the matrix of performance evaluation related to business process re-engineering as shown in table 2:

Table 2. Performance evaluation related to business process re-engineering

Performance feature related to business process re-engineering	Declaration
Number of generated associations.	Number of association rules that will be generated between the success factors of business process re-engineering and the performance of business process in the same dataset with constant values of confidence and support.
Interpretability	The ability to interpret and understand the associations generated in terms of business process re-engineering
Accuracy	$Accuracy = \frac{\text{no.of correct predictions}}{\text{total no.of predictions}}$ Accuracy difference $=$ $\lvert accurcy_{algroithm1} - accurcy_{algorithm2} \rvert$
Innovation	Increasing the level of interpretability of the associations generated and increasing their number leads to an increase in the level of innovation in interpretability new features related to the success factors of business process re-engineering and the performance of business processes.

3.5. Determining The Results

In this section, we will introduce the selected algorithms implementation results by using

python related to Number

of generated associations, Interpretability, Accuracy, and Innovation Shown in figures 2, 3, 4 :

Based on the results we should consider the business context. In the context of the BPR effort, we need to understand the associations generated between the success factors of the BPR process and the performance of the business processes. Therefore, we need to discover and interpret as many associations as possible in the dataset. Therefore, the previous selection effort included

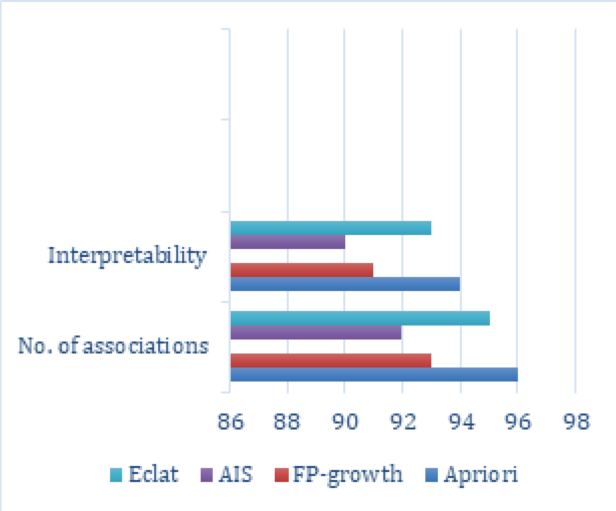

Figure 2. Results of Number of generated associations and Interpretability

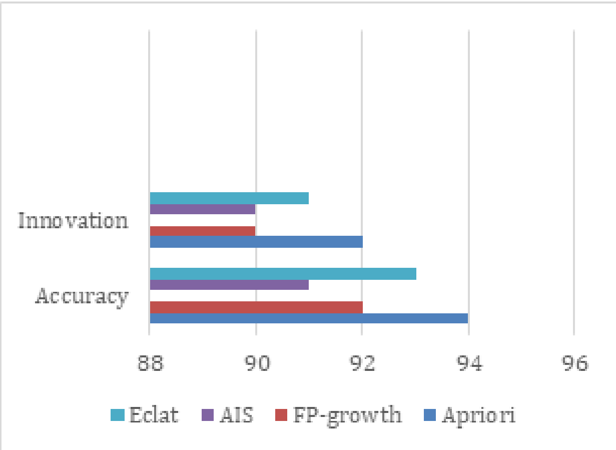

Figure 3. Results of innovation and Accuracy

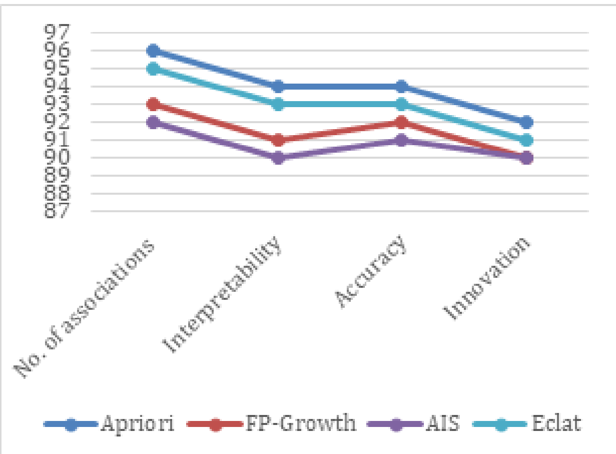

Figure 4. Results of Number of generated associations and Interpretability with accuracy and innovation

the following work contexts:

- Interpretability: we choose algorithms that provide easily understandable rules.
- Domain Relevance: we ensure the patterns align with business goals that are determined in first stage in this model.

In this model, these issues take up more space than other technical issues related to algorithms.

Also, in this section, we will summarize the findings based on the results: we should highlight strengths and weaknesses of each algorithm related to dataset of business process re-engineering. According to the results shown in the previous stages of this model, the Ariori algorithm is the most appropriate to use and generate associations in the case of a business process re-engineering dataset.

we introduce basic recommendation and suggest the best algorithm to use in business process re-engineering based on analysis is Apriori.

4. DISCUSSION

Re-engineering business processes is a complex issue. It has success factors of different dimensions. The critical issue in successfully integrating data mining techniques to aid in the success of the process re-engineering business process is a good understanding of several factors. Organizational structure, job satisfaction, increasing customer satisfaction, and preventing customer leakage from the organization are among the most important factors that lead to good business process re-engineering.

In this effort, we tried to generate the largest possible amount of understandable and interpretable associations in the business process re-engineering area by using dataset prepared to this propose in last studies. This effort may lay the foundation for the following future works:

- Developing an advanced business process re-engineering model.
- Developing and modifying the structure of the Apriori algorithm to undergo further special adaptation to generate a new algorithm intended for use in business process re-engineering models.

5. CONCLUSION

In this research, we presented an advanced evaluation model related to using the most appropriate algorithm in the business process re-engineering process. Initially, association rules field algorithms were the most appropriate for determining the relationship between the success factors of the business process re-engineering process. Because work processes are also built according to interconnected rules.

The basic algorithms in the field of association rules were chosen, which most modified algorithms for specific purposes were generated from , as follows: Apriori, FP-Growth, Eclat, AIS.

The selected algorithms were subjected to a proposed assessment model related to business process re-engineering. This model consists of mathematical examination of the structure of the selected algorithms and also an implementation aspect on a data set prepared in previous studies for the purpose of assisting in re-engineering business processes. This model consists of the following stages:

First stage: Data Preparation.

Second stage: Algorithm Selection:

- *Determine the mining pattern and algorithms.*
- *Make mathematical analysis of main association rules algorithms.*
- *Choose Candidates.*

Third stage: Implementation of selected algorithms

Fourth stage: Evaluate Performance.

Fifth stage: Determining The Results.

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