Improving Financial Technology (FinTech) in Banks Using Process Mining Algorithms

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Abstract-- **Many analysts believe that the future of the banking industry depends on the generalization and growth of fintechs. The growth and expansion of fintechs in the world indicate their importance in the banking industry. Today, it is important to know more about fintechs and its different parts [1]. Process mining is a new approach based on information technology that seeks to identify and improve the actual process model. Process mining is a chain of events encompassing the beginning and ending stages of a specific activity. Process mining aims to discover, monitor, and improve real-world processes by knowledge extraction from data stored in information systems. Process mining is on the list of new research disciplines, something between data mining and process modeling. In this method, the main ideas are very important, so discovering, monitoring, and enhancing business processes are three important factors in process mining science. This study contributes to the growing body of knowledge in process mining by highlighting the importance of adapting existing algorithms and methodologies to fit the specific needs and conditions of the banking industry, particularly in developing regions. In this research, in the first step, manual and system data related to the studied process were combined to ensure the comprehensiveness of the model, and the level of model details was adjusted based on the opinions of process owners before performing the mining process. After converting the integrated data file to the event log, the process model was implemented using ProM 5.2 and Genetics, Heuristics, Alpha ++, and Alpha algorithms. The results showed that the genetic algorithm has the best performance in issuing credit cards.**

Index Terms- **Fintech, Financial Technology, Process Mining, Banking, Mining Technique**

I. Introduction

FINTECH, due to the development of technology, the increasing penetration of the Internet, and the transformation of cyberspace in all aspects, the need for innovation in the financial application industry is increasingly felt. Fintech or financial technology is technological innovations aimed at improving financial performance [2]. Fintechs are proliferating, generating more revenue, and have a higher likelihood of lasting success [3]. Credit cards are one of the most important means of electronic money transfer in e-commerce, which are used instead of cash in payments. Although there are different types of bank cards, they are all known in Iran as credit cards. For this reason, the title of credit cards is used in this article. Cards are a means of exchanging money. For many years, money, coins, and then banknotes have been considered as the best means of payment due to their three characteristics convenience, simplicity, and speed of use. With the arrival of the industrial age, the growth of technical knowledge and the remarkable progress of societies, the increase in the volume of exchanges, and the consequent volume of liquidity, the need for an easier means of trading was felt and customers sought new ways to pay for their transactions. The evolution of people's behaviors and lifestyles and the public demand to use more facilities for payments made banks and financial institutions think of solutions. As a result of comprehensive efforts to meet customers' needs, a new means of payment emerged as credit cards [4]. Since the information systems' capabilities developed promisingly over the past five decades, this improvement led to a significant increase in the amount of data. In a changing environment, organizations must adapt their systems to existing processes in business process models using this data. A process is a set of codes, memory, data, and other resources that generate output by receiving input. This paper explores the process of business process management technology and aims to discover, analyze, control, and improve these processes by extracting knowledge from stored data (such as event data) available in information systems. The mining process focuses on developing creative techniques for analyzing these stored event data [5]. Recently, data scientists have noticed the exponential growth of data warehouses. They decided to turn this mass of data into concise and useful information. Part of this data was recorded behaviors of business processes. Monitoring these behaviors revealed that most of the problems of today's business processes are rooted in their past behaviors. Process mining techniques use this data to discover the actual process model and determine the

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differences between the original and actual process model (derived from real-world process behavior). As a result, deviations, bottlenecks, and errors of processes are identified at runtime and it is possible to analyze, eliminate, or improve them. In this way, the process model can be upgraded. However, with the available techniques and tools, the output of these algorithms is not entirely related to the business characteristics. Therefore, there is still a need for research and development on process mining science, techniques, and related tools [6]. In the last two decades, the business environment in the banking industry has become more competitive. The profit margins have decreased and customers want better and faster services. There are two approaches to increase the level of competitiveness of financial institutions. The first approach is outsourcing the selected processes to some companies and the second approach is to improve processes with a combination of organizational and IT-based metrics [7]. Most research in the field of process mining has presented different process mining algorithms and the practical applications of process mining have received less attention.

Process mining enables organizations to uncover their actual processes, provide insights, diagnose problems, and automatically trigger corrective actions. Process mining is an emerging scientific discipline positioned at the intersection between process science and data science [8]. Process mining is advancing as a powerful tool for revealing valuable insights about process dynamics [9]. Process mining (PM) is recognized as an effective discipline that provides tools and methods to get fact-based insights from past process executions stored in event logs and support process improvements [10]. Process mining techniques constitute an ideal means to tackle organizational challenges by suggesting process improvements and creating a company-wide process awareness [11]. Process mining solutions include enhancing performance, conserving resources, and alleviating bottlenecks in organizational contexts. However, as in other data mining fields, success hinges on data quality and availability [12].

A review of the research background shows that the application of process mining in the banking industry, especially in Iranian banks, has received less attention. Therefore, the purpose of this paper is to use process mining and specifically fuzzy mining algorithms in a real situation in the banking industry to evaluate the practical efficiency of process mining in this industry. It is worth noting that most of the processes in Iranian organizations, including banks, are not fully automated at present and at least part of the activities is performed and recorded manually. The lack of a database in which all events related to process activities are recorded is one of the main challenges of process mining in semi-automated processes. In such cases, relying solely on system data provides an incomplete picture of the process, and on the other hand, considering manually recorded data can affect the accuracy and validity of the extracted model. The main question of the present study is what is the most effective algorithm for issuing credit cards using the mining process?

II. RESEARCH BACKGROUND

used the mining process to discover the purchasing process in a financial institution to detect internal fraud [13]. However, their addressed process was not a specialized banking process, they just wanted to study fraud, and ignored the possible drawbacks of the process under study [7]. Evaluated the mining process in discovering the model of semi-automatic processes of the banking industry (studied the issuing process of bank guarantees). The efficiency of the mining process particularly the fuzzy mining algorithm has been investigated in discovering the semi-automatic processes. The PM2 methodology was used to implement the process mining project with changes in the first and fifth steps of the mentioned methodology. In the first step, manual and system data related to the studied process were combined to ensure the comprehensiveness of the model, and the level of model details was adjusted based on the opinions of the process owners before performing the mining process. After converting the integrated data file to the event log, the process model was discovered using ProM software and a fuzzy search algorithm. The use of manually recorded data can affect the results of the mining process. Therefore, in the validation step, in addition to the common criterion of compliance, a new criterion called expert-centered validation was defined, the value of which was 93% for the detection model. The results indicate that it is possible to use the algorithm of the studied process equal to 5 fuzzy minings in the case of a semi-automatic process [5].examined an approach to improve organizational processes using process mining techniques in the case study of the quality control process of Iranian national smart card applications. The purpose of this article is to provide an approach to improve organizational processes, using process mining techniques. This approach is presented by combining two models of process mining and business process life cycle, considering the relationship between an organization's processes, and evaluating by case study method. Accordingly, the quality control process of Iran's national smart card applications from the National Registration Organization has been selected for this purpose. The process's bottlenecks, deviations, and errors have been discovered by analyzing the event chart. Then, suggestions are presented for improving and solving the discovered problems [5].Examined the challenges in predicting business process monitoring methods. The purpose of this article was to review and compare the methods of predicting the process and existing challenges in this field and introduce, compare, and categorize the published articles in the field of process forecasting. Then, the process of research formation and the future direction of this field of research has been studied and explored by reviewing selected articles in this field. Moreover, this paper examined the status of the prediction methods in organizational architecture and methods of process improvement and reengineering.

III. RESEARCH METHOD

In this research, manual and system data related to the studied process were combined in the first step to ensure the comprehensiveness of the model, and the level of model details was adjusted based on the opinions of process owners before performing the mining process. After converting the integrated data file to the event log, the process model was developed using ProM 5.2 software and Genetics, Heuristics, Alpha ++, and Alpha algorithms. The results are based on the three systematic metrics of structure, precision, and fitness and the manual metric of generalization.

These algorithms have been selected based on their specific application and effectiveness in process mining, particularly in the context of credit card issuance. Each algorithm has unique strengths that make it suitable for different aspects of process mining:

Alpha Algorithm: Known for its simplicity and effectiveness in discovering process models from event logs.

Alpha++ Algorithm: An enhancement of the Alpha algorithm, which addresses some of its limitations in handling noise and incomplete data.

Genetic Algorithm: Recognized for its ability to optimize complex processes and adapt to changing conditions, making it particularly useful in dynamic environments like banking.

Heuristic Algorithm: Effective in finding solutions quickly, especially when dealing with large datasets, which is common in credit card issuance.

Calculation of the Generalization Metric:

The generalization metric is designed to evaluate how well a process model can be applied to unseen data or different contexts beyond the training dataset. It is calculated based on the following steps:

Model Training: Initially, the process model is trained using a specific dataset, which includes various event logs representative of the credit card issuance process.

Validation Dataset: A separate validation dataset is created, which contains event logs that were not included in the training phase. This dataset should ideally reflect the same process but may include variations or noise.

Performance Measurement: The generalization metric is computed by comparing the performance of the trained model on the validation dataset against its performance on the training dataset. Common performance indicators used in this comparison include accuracy, precision, and recall.

Generalization Score: The generalization score is then derived from the difference in performance metrics between the training and validation datasets. A smaller difference indicates better generalization, meaning the model is capable of accurately predicting outcomes in new, unseen scenarios.

Significance of the Generalization Metric:

The significance of the generalization metric lies in its ability to assess the robustness and applicability of the process model. A model that generalizes well is crucial in the context of credit card issuance, where processes may vary due to different customer profiles, regulatory changes, or operational adjustments.

Description of the Qg Parameter:

The Qg parameter is a measure of generalization quality in the context of process mining. It evaluates how well the developed process model can generalize to new, unseen data. A higher Qg value indicates better generalization capability, meaning the model is more likely to perform well in real-world scenarios.

Significance of Qg:

The Qg parameter is crucial for assessing the process model's robustness. By understanding how well the model generalizes, we can identify potential weaknesses and areas for improvement in the process mining techniques employed.

Calculation of Qg:

The Qg parameter is calculated using the following formula:

$$Qg = 1 - \left(\frac{1}{\sqrt{N_1}} + \frac{1}{\sqrt{N_2}} + \ldots + \frac{1}{\sqrt{N_k}}\right) \div k$$

Fig. 1. Calculation formula Qg

The Qg value is then calculated using the formula above, where we add up the reciprocals of the square roots of the events and divide by the total number of unique activities.

IV. COMPUTATIONAL RESULTS

A. *Alpha Algorithm*

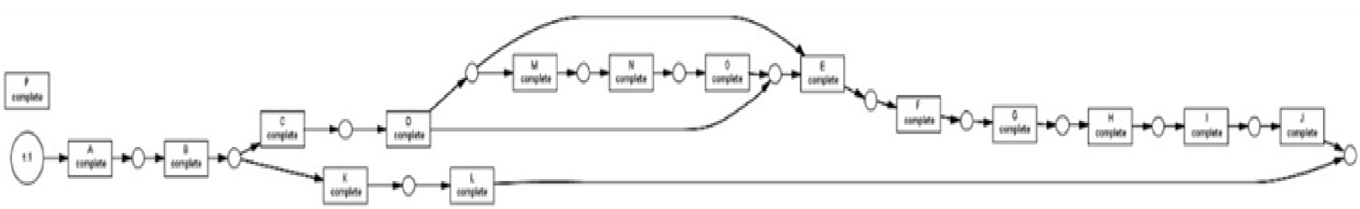

Fig. 2. Petri net resulting from implementing the Alpha algorithm on the model

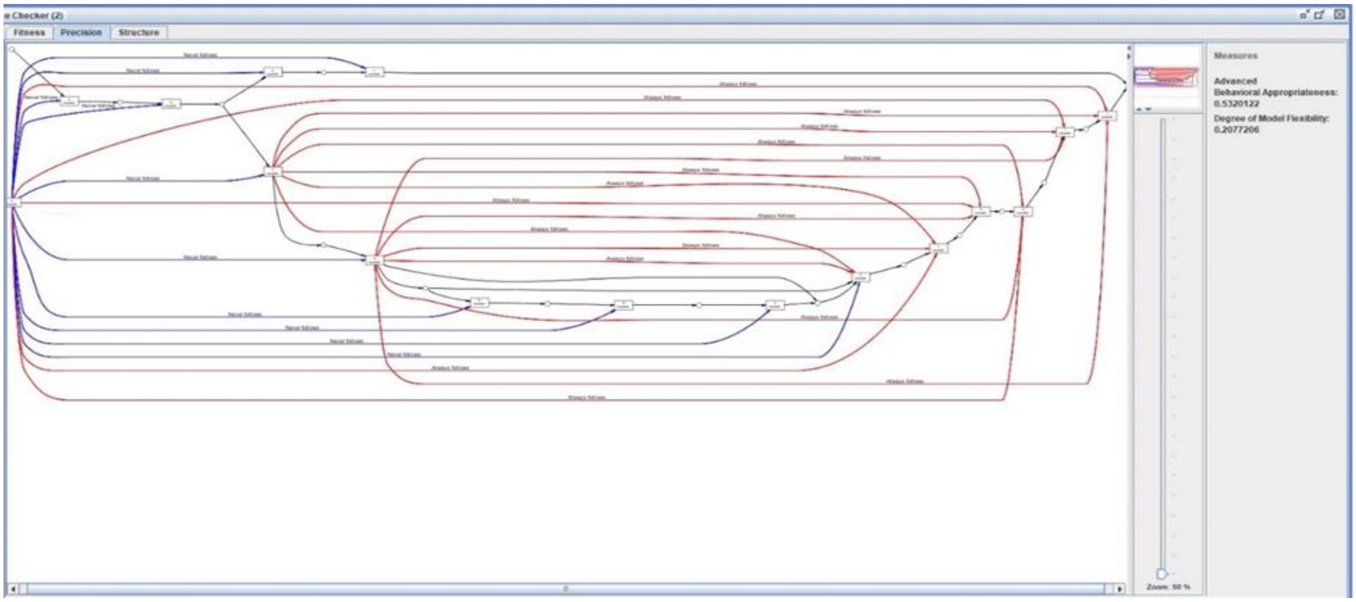

Fig. 3. Calculating precision obtained by running the Alpha algorithm on the model

Generalization Metric:

TABLE I
Trace1 Alpha Algorithm

Trace1	A	B	C	D	E	F	G	H	I	J
Model	A	B	C	D	E	F	G	H	I	J

TABLE II
Trace2 Alpha Algorithm

Trace2	A	B	K	L
Model	A	B	K	**L**

TABLE III
Trace3 Alpha Algorithm

Trace3	A	B	C	D	M	N	O	E	F	G	H	I	J
Model	A	B	C	D	M	N	O	E	F	G	H	I	**J**

TABLE IV
Trace4 Alpha Algorithm

Trace4	A	B	C	D	E	F	<<	F	G	H	I	J
Model	A	B	C	D	E	F	P	F	G	H	I	J

TABLE V
Calculation Result Alpha Algorithm

A = 89 + 35 + 42 + 24 = 190	I = 89 + 42 + 24 = 155
B = 89 + 35 + 42 + 24 = 190	J = 89 + 42 + 24 = 155
C = 89 + 42 + 24 = 155	K = 35
D = 89 + 42 + 24 = 155	L = 35
E = 89 + 42 + 24 = 155	M = 42
F = 89 + 24 = 113	N = 42
G = 89 + 42 + 24 = 155	O = 42
H = 89 + 42 + 24 = 155	P = 0

$$Q_g = 1 - \left(\frac{\frac{1}{\sqrt{190}}+\frac{1}{\sqrt{190}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{113}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{35}}+\frac{1}{\sqrt{35}}+\frac{1}{\sqrt{42}}+\frac{1}{\sqrt{42}}+\frac{1}{\sqrt{42}}}{16} \right) = 0.987$$

B. Alpha ++ Algorithm

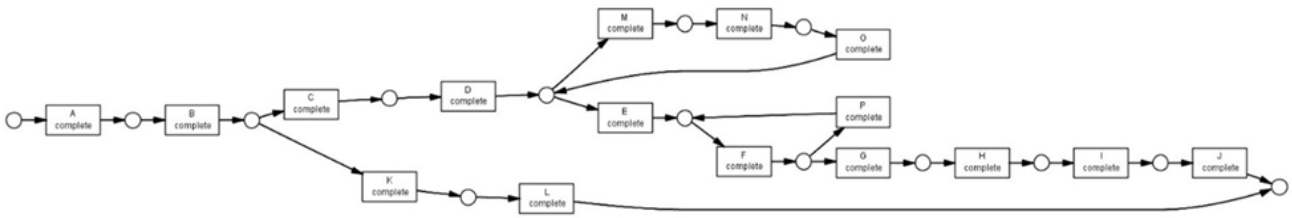

Fig. 4. Petri net resulting from implementing the Alpha++ algorithm on the model

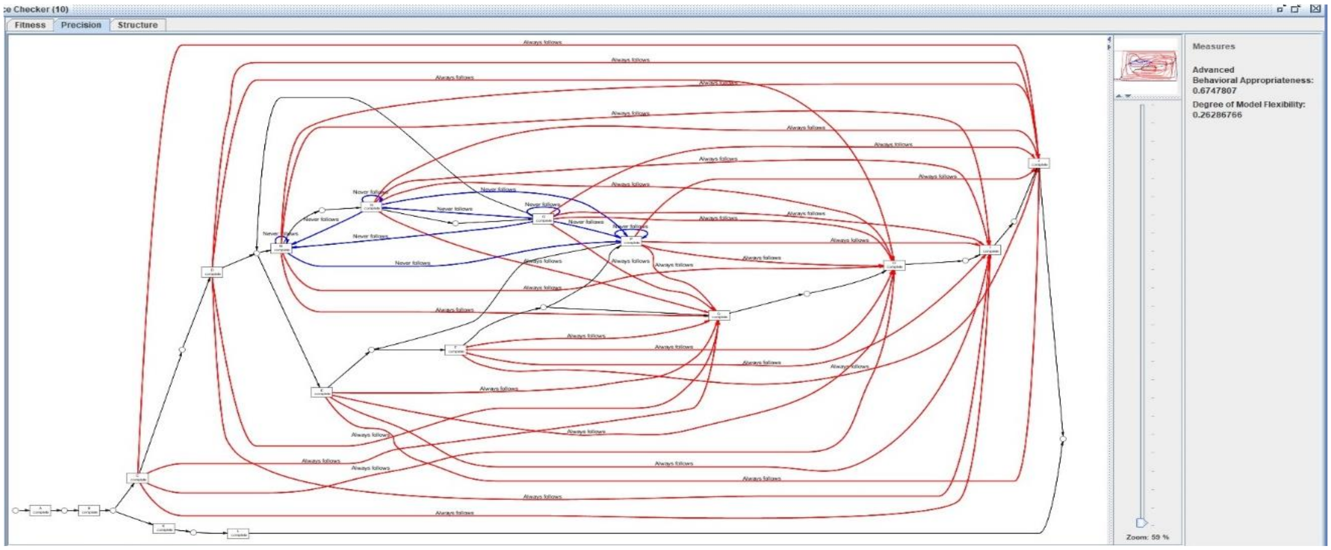

Fig. 5. Calculating precision obtained by running the Alpha++ algorithm on the model

Generalization Metric:

TABLE VI
Trace1 Alpha++Algorithm

Trace1	A	B	C	D	E	F	G	H	I	J
Model	A	B	C	D	E	F	G	H	I	J

TABLE VII
Trace2 Alpha++ Algorithm

Trace2	A	B	K	L
Model	A	B	K	L

TABLE VIII
Trace3 Alpha++Algorithm

Trace3	A	B	C	D	M	N	O	E	F	G	H	I	J
Model	A	B	C	D	M	N	O	E	F	G	H	I	J

TABLE IX
Trace4 Alpha++ Algorithm

Trace4	A	B	C	D	E	F	P	F	G	H	I	J
Model	A	B	C	D	E	F	P	F	G	H	I	J

TABLE X
Trace5 Alpha++ Algorithm

A = 89 + 35 + 42 + 24 = 190	I = 89 + 42 + 24 = 155
B = 89 + 35 + 42 + 24 = 190	J = 89 + 42 + 24 = 155

TABLE XI
Calculation Result Alpha++ Algorithm

C = 89 + 42 + 24 = 155	K = 35
D = 89 + 42 + 24 = 155	L = 35
E = 89 + 42 + 24 = 155	M = 42
F = 89 + 42 + 24 = 155	N = 42
G = 89 + 42 + 24 = 155	O = 42
H = 89 + 42 + 24 = 155	P = 24

$$Q_g = 1 - \left(\frac{\frac{1}{\sqrt{190}} + \frac{1}{\sqrt{190}} + \frac{1}{\sqrt{155}} + \frac{1}{\sqrt{155}} + \frac{1}{\sqrt{155}} + \frac{1}{\sqrt{155}} + \frac{1}{\sqrt{155}} + \frac{1}{\sqrt{155}} + \frac{1}{\sqrt{155}} + \frac{1}{\sqrt{155}} + \frac{1}{\sqrt{35}} + \frac{1}{\sqrt{35}} + \frac{1}{\sqrt{42}} + \frac{1}{\sqrt{42}} + \frac{1}{\sqrt{42}} + \frac{1}{\sqrt{24}}}{16} \right) = 0.985$$

C. Genetic Algorithm

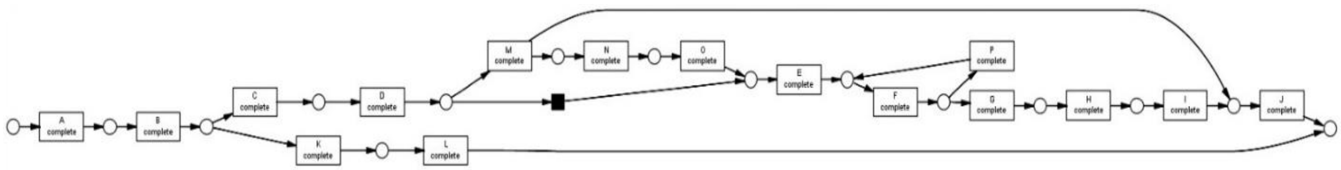

Fig. 6. Petri net resulting from implementing the Genetic algorithm on the model

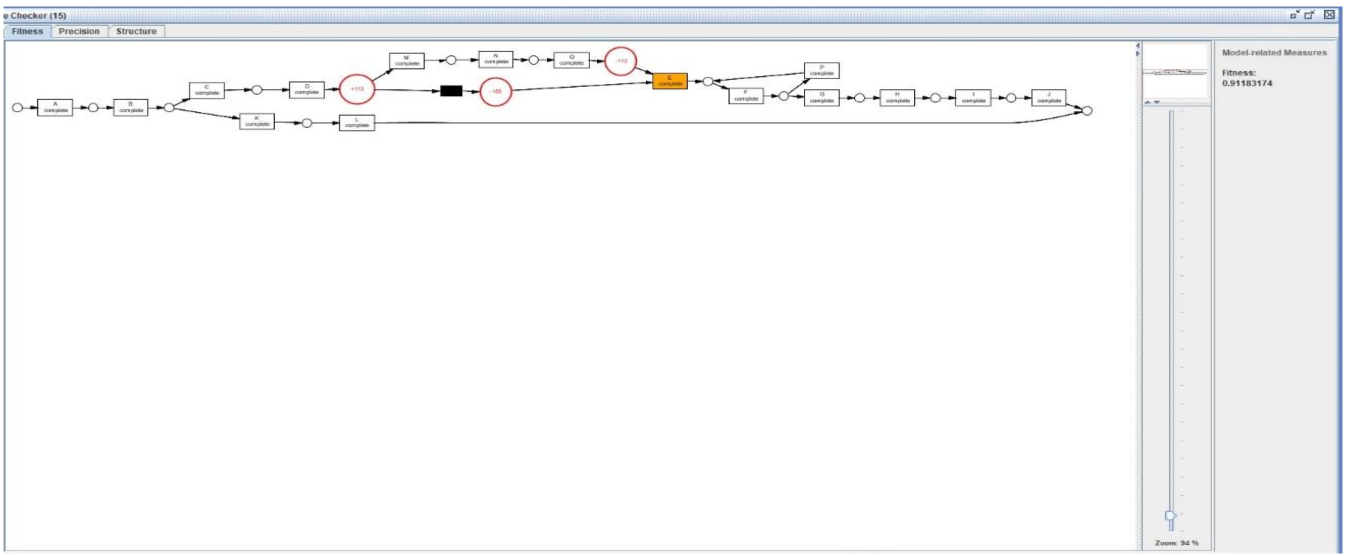

Fig. 7. Calculating fitness obtained by running a Genetic algorithm on the model

Generalization Metric:

TABLE XII
Trace1 Genetic Algorithm

Trace1	A	B	C	D	E	F	G	H	I	J
Model	A	B	C	D	E	F	G	H	I	J

TABLE XIII
Trace2 Genetic Algorithm

Trace2	A	B	K	L
Model	A	B	K	L

TABLE XIV
Trace3 Genetic Algorithm

Trace3	A	B	C	D	M	N	O	E	F	G	H	I	J
Model	A	B	C	D	M	N	O	E	F	G	H	I	J

TABLE XV
Trace4 Genetic Algorithm

Trace4	A	B	C	D	E	F	P	F	G	H	I	C
Model	A	B	C	D	E	F	P	F	G	H	I	J

TABLE XVI
The Calculation Results in the Genetic Algorithm

A = 89 + 35 + 42 + 24 = 190	I = 89 + 42 + 24 = 155
B = 89 + 35 + 42 + 24 = 190	J = 89 + 42 + 24 = 155
C = 89 + 42 + 24 = 155	K = 35

D = 89 + 42 + 24 = 155	L = 35
E = 89 + 42 + 24 = 155	M = 42
F = 89 + 42 + 24 = 155	N = 42
G = 89 + 42 + 24 = 155	O = 42
H = 89 + 42 + 24 = 155	P = 24

$$Q_g = 1 - \left(\frac{\frac{1}{\sqrt{190}}+\frac{1}{\sqrt{190}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{35}}+\frac{1}{\sqrt{35}}+\frac{1}{\sqrt{42}}+\frac{1}{\sqrt{42}}+\frac{1}{\sqrt{42}}+\frac{1}{\sqrt{24}}}{16}\right) = 0.985$$

D. Heuristics Algorithm

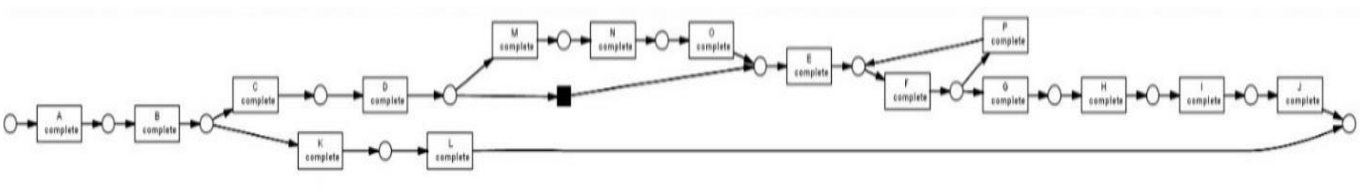

Fig. 8. Petri net resulting from implementing the Heuristics algorithm on the model

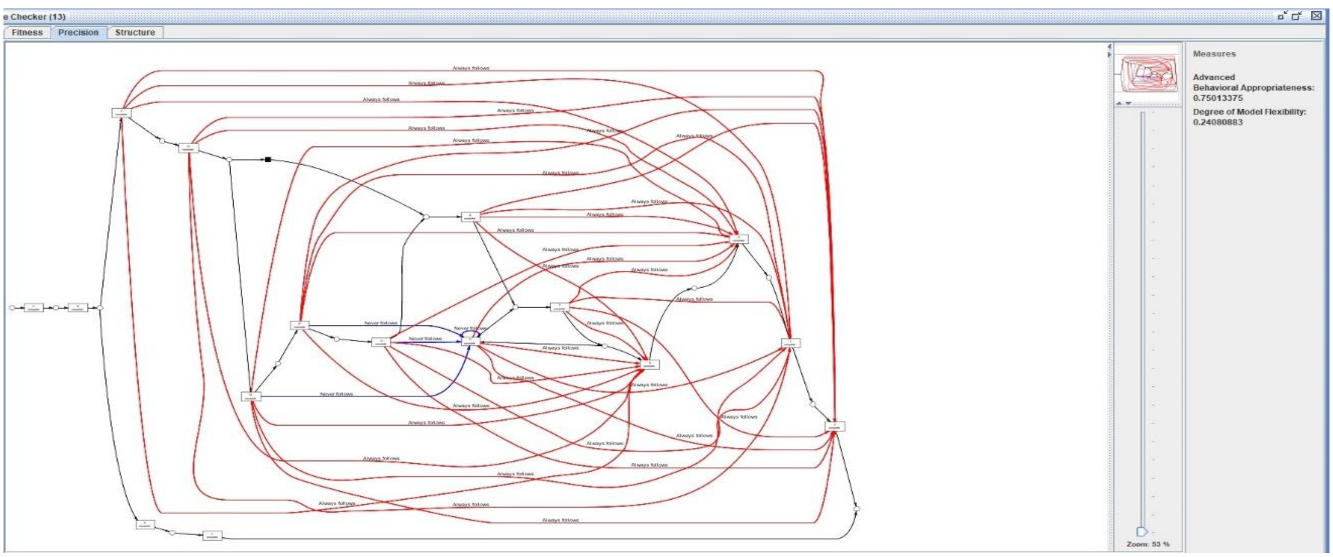

Fig. 9. Calculating precision obtained by running the Heuristics algorithm on the model

Generalization Metric:

TABLE XVII
Trace1 Heuristics Algorithm

Trace1	A	B	C	D	E	F	G	H	I	J
Model	A	B	C	D	E	F	G	H	I	J

TABLE XVIII
Trace2 Heuristics Algorithm

Trace2	A	B	K	L
Model	A	B	K	L

TABLE XIX
Trace3 Heuristics Algorithm

Trace3	A	B	C	D	M	N	O	E	F	G	H	I	J
Model	A	B	C	D	M	N	O	E	F	G	H	I	J

TABLE XX
Trace4 Heuristics Algorithm

Trace4	A	B	C	D	E	F	P	F	G	H	I	J
Model	A	B	C	D	E	F	P	F	G	H	I	J

TABLE XXI
Trace5 Heuristics Algorithm

A = 89 + 35 + 42 + 24 = 190	I = 89 + 42 + 24 = 155
B = 89 + 35 + 42 + 24 = 190	J = 89 + 42 + 24 = 155
C = 89 + 42 + 24 = 155	K = 35
D = 89 + 42 + 24 = 155	L = 35
E = 89 + 42 + 24 = 155	M = 42
F = 89 + 42 + 24 = 155	N = 42
G = 89 + 42 + 24 = 155	O = 42
H = 89 + 42 + 24 = 155	P = 24

$$Q_g = 1 - \left(\frac{\frac{1}{\sqrt{190}}+\frac{1}{\sqrt{190}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{155}}+\frac{1}{\sqrt{35}}+\frac{1}{\sqrt{35}}+\frac{1}{\sqrt{42}}+\frac{1}{\sqrt{42}}+\frac{1}{\sqrt{42}}+\frac{1}{\sqrt{24}}}{16}\right) = 0.985$$

The results of all four algorithms show that the genetic algorithm has a better performance.

TABLE XXII
Comparing the Results of Algorithms on the Model

Algorithm	Fitness	Precision	Structure	Generalization	Overall
Genetics	0.91	1	1	0.985	0.973
Heuristics	1	0.75	1	0.987	0.934
Alpha++	1	0.67	1	0.985	0.913
Alpha	0.96	0.53	1	0.985	0.868

Also, the Event Log of issuing the credit card of the opened account is as follows.

TABLE XXIII
Event Log of Issuing the Credit Card of the Opened Account

Case ID	Task Name	User	Timestamp	Agent	Description	Activity
1000	Upload Documents	Reza Saket	11/4/2024 9:00	Internal System	Uploading customer documents	A
1000	Send Files	Reza Saket	11/4/2024 9:14	Internal System	Sending documents	B
1000	Receive Successful Message	Reza Saket	11/4/2024 9:15	Internal System	Receiving the confirmation message	C
1000	Registration Inquiry	Jafar Dianat	11/4/2024 9:25	Bank	Registration inquiry	D
1000	Positive Authentication	Mehdi Bayat	11/4/2024 9:26	Registry Office	Positive authentication	E
1000	Card Issuance	Jafar Dianat	12/4/2024 9:45	Bank	Card issuance	F
1000	Card Activation	Jafar Dianat	12/4/2024 9:51	Bank	Card activation	G
1000	Send Card	Jafar Dianat	12/4/2024 11:00	Bank	Sending the card to the center	H
1000	Send SMS	Jafar Dianat	12/4/2024 11:01	Bank	Sending a confirmation message on receiving the card	I
1000	Receive Card	Reza Saket	13/4/2024 13:05	Internal User	Receiving the card from the bank	J
1001	Upload Document	Arian Ghazi	11/4/2024 8:15	Internal User	Uploading customer documents	A
1001	Send Files	Arian Ghazi	11/4/2024 8:25	Internal User	Sending documents	B
1001	Receive Unsuccessful Message	Arian Ghazi	11/4/2024 8:28	Internal User	Receiving unsuccessful message	K
1001	Case Closed	Headquarter	11/4/2024 8:28	Bank	Closing the case	L
1002	Upload Documents	Kamran Daei	11/4/2024 8:40	Internal System	Uploading documents	A
1002	Send Files	Kamran Daei	11/4/2024 8:55	Internal System	Sending documents	B
1002	Receive Successful Message	Kamran Daei	11/4/2024 8:56	Internal System	Receiving successful message	C
1002	Registration Inquiry	Jafar Dianat	11/4/2024 9:05	Bank	Registration inquiry	D

1002	Negative Authentication	Mehdi Bayat	11/4/2024 9:10	Registry Office	Negative Authentication	M
1002	Request Information	Mehdi Bayat	11/4/2024 9:11	Registry Office	Requesting information	N
1002	Send Customer Info	Jafar Dianat	11/4/2024 9:15	Bank	Resending customer info	O
1002	Positive Authentication	Mehdi Bayat	11/4/2024 9:16	Registry Office	Positive Authentication	E
1002	Card Issuance	Jafar Dianat	12/4/2024 9:40	Bank	Card Issuance	F
1002	Card Activation	Jafar Dianat	12/4/2024 9:41	Bank	Card Activation	G
1002	Send Card	Jafar Dianat	12/4/2024 11:00	Bank	Sending a card to the center	H
1002	Send SMS	Jafar Dianat	12/4/2024 11:01	Bank	Sending a confirmation message on receiving the card	I
1002	Receive Card	Kamran Daei	13/4/2024 12:30	Internal User	Receiving the card	J
1003	Upload Documents	Maryam Salimi	11/4/2024 10:15	Internal System	Uploading customer documents	A
1003	Send Files	Maryam Salimi	11/4/2024 10:32	Internal System	Sending documents	B
1003	Receive Successful Message	Maryam Salimi	11/4/2024 10:33	Internal System	Receiving a confirmation message	C
1003	Registration inquiry	Jafar Dianat	11/4/2024 10:40	Bank	Registration inquiry	D
1003	Positive Authentication	Mehdi Bayat	11/4/2024 10:42	Registry Office	Positive Authentication	E
1003	Card Issuance	Jafar Dianat	12/4/2024 10:50	Bank	Card Issuance	F
1003	Failure Card Activation	Jafar Dianat	12/4/2024 10:55	Bank	Card Activation Failure	P
1003	Card Issuance	Jafar Dianat	12/4/2024 11:00	Bank	Card Issuance	F
1003	Card Activation	Jafar Dianat	12/4/2024 11:02	Bank	Card Activation	G
1003	Send Card	Jafar Dianat	12/4/2024 11:30	Bank	Sending a card to the center	H
1003	Send SMS	Jafar Dianat	12/4/2024 12:00	Bank	Sending a confirmation message on receiving the card	I
1003	Receive Card	Maryam Salimi	13/4/2024 14:00	Internal User	Receiving the card	J

TABLE XXIV
Sequences

Case ID	Trace	Count
1000	{A, B, C, D, E, F, G, H, I, J}	89
1001	{A, B, K, L}	35
1002	{A, B, C, D, M, N, O, E, F, G, H, I, J}	42
1003	{A, B, C, D, E, F, P, F, G, H, I, J}	24

V. CONCLUSION

The process mining cycle summarizes the various factors required to achieve process maturity brings a level of organizational understanding that provides the organization with the necessary transparency and insight, and prepares it for scaling.

Process mining is an intelligent approach to discover and prove processes to discover semi-automatic or manual process models in addition to the fully automatic process model. Organizations gain the ability to understand, continuously improve, and control processes by adapting process mining to their systems. Unwanted risks and hidden opportunities can be easily identified by detecting the actual stream of processes; therefore, corrective actions can save time and money. This approach uses real-world events and provides the data needed to redesign business processes. Using process mining techniques, a lot of information is collected about the implementation of processes such as decision patterns, flow control, performance, etc. It is also possible to create simulation models in a process model. Examining the results of all four algorithms shows that the genetic algorithm has a better performance.

A. Challenges Encountered

Data Inconsistency: Manual data entries often suffer from inconsistencies due to human error, variations in data recording practices, and lack of standardization. This inconsistency can lead to discrepancies when compared to system-generated data, which is typically more uniform and structured.

Data Completeness: In many cases, not all events related to the process are captured in the system. Manual entries may fill in gaps, but they can also introduce biases or incomplete information, affecting the overall integrity of the dataset.

Temporal Alignment: Synchronizing timestamps between manual and system data can be challenging. If manual entries are recorded at different times or lack precise timestamps, it becomes difficult to accurately represent the sequence of events in the process.

Validation of Manual Data: Ensuring the accuracy of manually recorded data is a significant challenge. We relied on expert validation to assess the quality of this data, but subjective interpretations can still influence the results.

B. Impact on Results

These challenges in combining manual and system data may have impacted our results in several ways:

Model Accuracy: The presence of inconsistencies and incomplete data could lead to a less accurate representation of the actual process model. This may affect the precision and fitness metrics we reported.

Generalization Capability: The generalization metric could also be influenced by the quality of the combined dataset. If the model is trained on data that includes significant noise or inaccuracies, its performance on unseen data may not reflect its true capability.

Identifying Bottlenecks: The integration of manual data is essential for identifying bottlenecks and deviations in the process. However, if the manual data is not reliable, it may obscure critical insights that could have been discovered through a more accurate dataset.

Also suggests that future research should explore more robust methods for combining manual and system data to enhance the effectiveness of process mining in semi-automated environments.

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