IJCCS (Indonesian Journal of Computing and Cybernetics Systems)
Vol.18, No.1, January 2024, pp. 61~72
ISSN (print): 1978-1520, ISSN (online): 2460-7258
DOI: https://doi.org/10.22146/ijccs.90030

Modeling OTP Delivery Notification Status through a Causality and Apriori

Novendri Isra Asriny*[1], Chandra Kusuma Dewa[2], Ahmad Luthfi[3]
[1]Master of Informatics, Universitas Islam Indonesia, Yogykakarta, Indonesia
[2,3]Dept. of Information Technology, Universitas Islam Indonesia, Yogyakarta, Indonesia
e-mail: ***[1]21917037@students.uii.ac.id**, [2]chandra.kusuma@uii.ac.id, [3]ahmad.luthfi@uii.ac.id

Abstrak

Kekuatan utama dibalik perekonomian modern saat ini adalah uang digital, ada banyak bentuk metode pembayaran tanpa kontak langsung yang tersedia saat ini, termasuk kartu kredit/debit, dompet elektronik, dan lainnya. Hal ini meningkat pula resiko kerentanan keamanan terkait kata sandi dalam transaksi online. Alternatif untuk memitigasinya yakni kata sandi satu kali yang muncul untuk mengurangi hal ini. Untuk setiap sesi otentikasi pengguna, kata sandi satu kali (OTP) adalah mekanisme otentikasi kata sandi atau validasi tambahan. Setiap kali pengiriman SMS kata sandi OTP memungkinkan terjadinya kegagalan baik karena masalah jaringan operator atau masalah teknis. Maka, perlu untuk mengevaluasi kausalitas kategori status pengiriman transaksi pengiriman SMS one-time password agar dapat meminimalisir nilai resiko yang timbul pada transaksi online dengan menentukan faktor utama pengiriman SMS OTP berhasil atau tidak, serta apa yang menyebabkan kegagalan saat mengirim SMS OTP menggunakan metode Bayesian Network. Didapatkan hasil bahwa dari data, transaksi online lebih banyak terjadi pada saat pagi hari dengan ringkasan status tidak delay, tidak diketahui ringkasan status, dan lainnya. Selain itu, ringkasan status utama yang memiliki kausalitas setidaknya ke 3 variabel yakni tidak delay, ringkasan tidak diketahui, penundaan lama, normal, kemungkinan masalah operator, tidak normal, dan lain-lain. Dengan keakurasian yang tinggi ~90% dalam memprediksi probabilitas terjadi.

Keywords*—transaksi online, one-time password, transaksi SMS, machine learning, bayesian network.*

Abstract

Digital money is the fundamental driving factor behind today's modern economy. Credit/debit cards, e-wallets, and other contactless payment options are widely available nowadays. This also raises the security risk associated with passwords in online transactions. One-time passwords (OTPs) are another option for mitigating this. A one-time password (OTP) is an additional password authentication or validation technique for each user authentication session. Failures in transmitting OTP passwords through SMS can arise owing to operator network faults or technological concerns. To minimize the risk value in online transactions, it is necessary to evaluate the causality of the OTP SMS sending transaction status category by determining the main factors for successful OTP SMS sending and identifying the causes of failure when sending it using the Bayesian Network method. According to data analysis, online transactions occur more frequently in the morning, with status summaries such as no delay, unknown status, etc. Furthermore, there is causality with at least three variables in the principal status summary: no delay, uncertain summary, long delay, normal, likely operator issues, and abnormal. With a high accuracy rate of around 90% in forecasting the likelihood of recurrence.

Keywords— *online transaction, one-time password, SMS transaction, machine learning, bayesian network.*

Received October 23th,2023; Revised October 28th, 2023; Accepted January 5th, 2024

1. INTRODUCTION

The internet has developed exceptionally quickly up to this point, and many innovations have appeared, such as transportation service providers, online shop services, and many more services that pamper customers who are increasingly unable to live without their cell phones. In addition, several electronic payment options, including credit/debit cards, e-wallets, and other direct contactless payment methods, have arisen [1].

Based on data from [2], the use of e-wallets increased significantly in 2020, giving rise to the QRIS product, which allows interoperability between e-wallet providers and users in daily transactions.

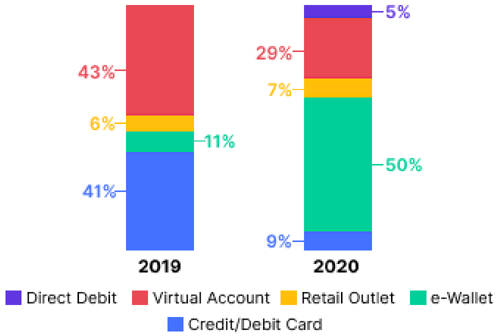

Figure 1 Transactions based on payment method.

There are many security issues regarding passwords, including password theft, which is becoming widespread, especially in online transactions. Based on [3], it is known that the number of internet users worldwide has increased, and the number of cyber threats or attacks also follows this increase. There were 12.8 million attacks recorded in 2018 in Indonesia, growing significantly in 2019 to 98.2 million attacks and in 2020 to 74.2 million. Then, based on a report [4], it is known that suspected data leaks throughout 2022 fluctuate every month and increase significantly in September with 119 suspected data breach incidents. In total, during 2022, BSSN has detected 311 suspected data breach incidents in 248 stakeholders.

As a result, many businesses are turning to alternative approaches such as one-time passwords (OTPs), which are only suitable for authenticating users in one session to increase the level of security for users [5].

A one-time Password (OTP) is a password authentication scheme or additional validation used for each user authentication session. It is no longer valid if the authentication session has expired or a one-time password has been used. The advantages of using OTP are [6]: A password different from the previous one is safe from attacks that want to use the last password because it is no longer valid to log in for future sessions. Generally, OTP is received via SMS, so there is no need to have access to email. OTP allows companies to improve user experience and reduce operational costs because users are already familiar with mobile phones and do not need additional devices to receive codes.

Machine learning relieves humans of the burden of explaining and formalizing their knowledge into a machine-accessible form and allows it to be developed efficiently through intelligent systems. Machine learning describes a system's capacity to learn from historical data to automate building analytical models and completing related tasks. In parallel, deep learning constitutes a subfield within machine learning founded upon the principles of artificial neural networks. In many applications, models generated from deep learning outperform machine learning models and traditional data analysis approaches [7].

This research will use Bayesian network methods to classify SMS data based on OTP SMS sending status using One-Time Password SMS sending transaction data in Indonesia from July to November 2021. In stages, this research begins by knowing the characteristics first to get a general picture of the data condition used, then continues with selecting the status summary category variables used and learning about cause and effect.

According to the literature review conducted on [8]–[12], no one has reviewed the OTP short message sent using the Bayesian network statistical approach to get some significant variables from cause and effect, and the literature review solely assesses systems, processes, and recommendations for new OTP alternatives approach also Bayesian networks are used on other research objects. Aside from that, the a priori algorithm is used as a comparison in this research to determine the method or algorithm used to get the method's reliability in this case study.

2. METHOD

In this study, researchers used some research variables, including Summary Status (Not Delay Notification, Very Normal Notification, Unknown Summary Notification, Normal Delay Notification, Long Delay Notification, Maybe Delay Notification From Third Party, Normal Notification, Timeout to Third Party, Average Delay Notification, Maybe Issue From Operator, Not Normal Notification), supported by several other variables, including Delivered Category, Undelivered Category, Average Notification per Minutes, and As opposed to the data distribution strategy, which uses a normal distribution, this category results from binning datasets on an interval data scale using a percentile approach. These two strategies (division and distribution) deal with severe data abnormalities [13].

2.1 Data Preparation

A dataset of OTP user transactions in Indonesia is used in this study. The data period used is July 2021 to November 2021, with 259 thousand data transactions per hour. Company X (OTP SMS delivery service provider) also makes four supporting variables and ten status categories accessible. Company X, a provider of OTP messaging services, is the direct source from which transaction data is collected. In terms of data distribution, this study concluded that 80% of the data were used for training, and 20% were used for testing utilizing experimental judgment and primary data.

2.2 Bayesian Network

A graphical representation of the probability correlations between essential variables is a Bayesian network. Graphical models have some advantages when used with statistical data modeling methods. First, because it incorporates interdependence between all variables, the model is easily adaptable to cases where some data entries are missing. Additionally, one can comprehend issue regions and calculate the repercussions of an activity by employing a Bayesian Network to examine cause-and-effect relationships. Then, because models include causal and probabilistic semantics, they are ideal for fusing prior knowledge (which frequently takes the form of causal links) with data. Lastly, integrating Bayesian statistical methods with Bayesian Networks is valuable and successful in avoiding data overfitting [14].

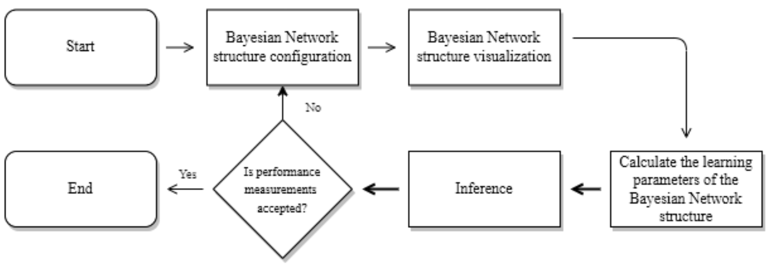

Figure 2 Summary Flowchart Bayesian Network [15].

2.2.1 Conditional Probability Distributions (CPDs)

A lot of work in probability and statistics is concerned with deriving probabilities and conditional distributions in specific circumstances, with each situation frequently requiring particular insight into the structure of the answer, particularly when probabilities and conditional distributions are desired to be defined. as in Bayesian statistical applications at points [16].

$$P(B|A) = \frac{P(B \cap A)}{P(A)} \tag{1}$$

Information :

$P(B|A)$: Reflects the conditional probability that event B will occur if event A occurs.
$P(B \cap A)$: The probability of both A and B happening at the same time
$P(A)$: The probabilty of event A

2.3 Apriori Algorithm

Association rules are rules that learn objects or traits that always come together. Association rules are designed to assess all if-then links between items and select only the most likely (most likely) evidence of dependence ties between items. Typically, the terms antecedent and consequent express the IF and THEN parts of the equation. Antecedents and outcomes are a group of items in this analysis that do not share a common link [17]. The approach in this a priori method is divided into two stages: generating frequent itemsets [support] (itemsets with more supports than minsup are acquired) and generating rules [confidence] (rules with greater confidences than minconf are chosen from among the frequent itemsets obtained in the first stage).

$$\boldsymbol{Support}\ (\boldsymbol{A} \rightarrow \boldsymbol{B}) = \frac{\boldsymbol{Transaction}(\boldsymbol{A} \cup \boldsymbol{B})}{\boldsymbol{N}} \tag{2}$$

$$\boldsymbol{Confidence}\ (\boldsymbol{A} \rightarrow \boldsymbol{B}) = \frac{\boldsymbol{Support}(\boldsymbol{A} \cup \boldsymbol{B})}{\boldsymbol{Support}(\boldsymbol{A})} \tag{3}$$

Information :

N : Total the transactions
Support $(A \rightarrow B)$: Illustrates an association rule with A as the antecedent (if) and B as the result (then).
$A \cup B$: The group of transactions that contain both A and B
Support $(A \cup B)$: The aggregate group of support the number of transactions in which both A and B are present.
Support (A) : The support of the group of objects A, the number of transactions that contain A

2.4 Evaluation of Bayesian Network

The number of items accurately identified by the model serves as an indicator of precision. The precision value ranges from 0 to 1, with higher precision values indicating greater object detection accuracy for the model. Precision can be described as the percentage of recommended things (relevant + irrelevant items) that are relevant. Recall counts the number of objects the model correctly identified out of all the ones it was supposed to. The recall value ranges from 0 to 1, and the higher the recall value, the more items the model can detect with success. Recall is used to gauge how relevant the system's output is. An evaluation statistic for models called the F1 score combines recall and precision. The F1 score ranges from 0 to 1, with a higher F1 score indicating more extraordinary model performance. The harmonic mean of recall and precision is the F1 score. As a result, it symmetrically combines recall and precision into one metric. The F beta score gives one precision or recall more weight than the other and is becoming increasingly prevalent [18]. Accuracy is measured by comparing the correct guesses or data predictions to the whole set of data [19].

$$Precision = \frac{TruePositive}{(TruePositive + FalsePositive)} \tag{4}$$

$$Recall = \frac{TruePositive}{(TruePositive + FalseNegative)} \tag{5}$$

$$F1 - Score = \frac{2\ x\ (Recall\ x\ Precision)}{(Recall + Precision)} \tag{6}$$

$$Accuracy = \frac{(TruePositive + TrueNegative)}{(TruePositive + FalsePositive + FalseNegative + TrueNegative)} \tag{7}$$

3. RESULT AND DISCUSSION

3.1 Exploratory Data Analysis

This exploratory data analysis aims to gain a general understanding of the dataset's characteristics. The following are the results obtained.

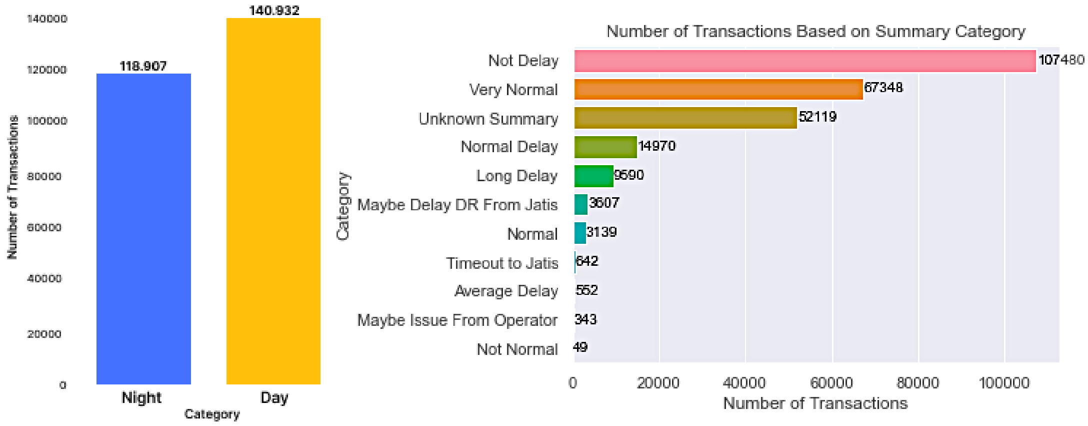

Figure 3 (a) Number of Transactions Based on Time Category. (b) Number of Transactions Based on Status of Summary Category

Based on Figure 3 points a and b, it can be seen that most transactions are carried out in the morning (54.2%), while transactions are carried out in the evening (45.76%). Also, it can be seen that the OTP message-sending transactions in the top 2 are delivered smoothly (No delay [41.36%], Very Normal [25.92%]), but the status in the 3rd rank is unknown (between delivery failures from the 3rd party to the operator or from the operator sending the status to a 3rd party) amounting to 20.06%.

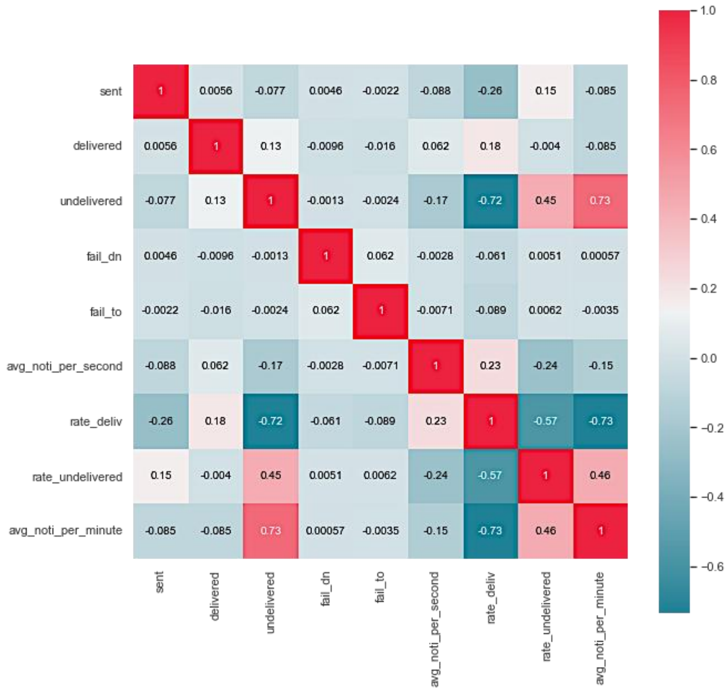

Figure 4 Correlation Between OTP Message Delivery Transaction Status Summary Variables

Based on Figure 4, it can be seen that the variables that have a strong relationship are delivery rate with undelivered (-72%), then average notifications per minute with undelivered (73%), and average notifications per minute with delivery rate (-73%). Meanwhile, those that have a weak correlation are the undelivered rate with the delivery rate (-57%), the average notification per minute with the undelivery rate (46%), the undelivered rate with the undelivered (45%), the delivery rate with the average notification per second (23%) undelivered rate with average notifications per second (-24%), and average notifications per minute with average notifications per second (-15%).

3.2 Reliability Methods

Finding the best approach to use in the current case study, this research also evaluates the validity of the a priori algorithm and the Bayesian network method.

For each method's accuracy and confidence values, the a priori algorithm employs confidence values, and the Bayesian network method uses accuracy values to compare these two approaches [20].

Table 1 Average Value of Reliability Methods

Method	Avg. Value of Reliability
Bayesian Network	86,70%
Apriori Algorithm	72,25%

Table 1 illustrates that, on average, the Bayesian network's dependability value is higher than the a priori algorithm method's. In addition to its higher reliability value, the Bayesian network method based on [21] has the following advantages: the Bayesian Network approach can be used to provide a subjective interestingness score, which indicates that when the majority of the patterns from the historical data diverge, the Bayesian network may find the data to be fascinating. Afterward, these intriguing patterns can also be applied to learning, allowing the Bayesian Network to explicitly exploit the dataset in situations when expert opinion is lacking by using the DAG structure to explain the data. Fewer redundant variables unrelated to the variable of interest will be eliminated if a DAG structure exists. Meanwhile, the Apriori method produces association rules in the form of "if-then" statements, making them understandable to users who may not be familiar with probabilistic graphical models.

3.3 Bayesian Network

Bayesian networks are used in this research to reduce the variables used in this research; apart from that, by using this method, you can explore the variables that have a causal relationship.

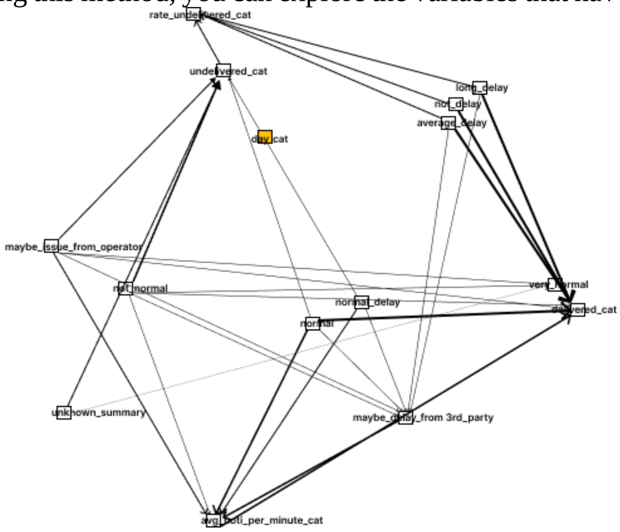

Figure 5 Network visualization from the Bayesian Network model

Based on Figure 5, it can be seen that the parent variables are the undelivered category, rate undelivered category, average notification per minutes category, status maybe delayed from 3rd party, very normal status, and delivered category. The undelivered category is influenced by possible issue status from the operator, not normal status, unknown summary status, day category, and normal status. The average notification per minute category is influenced by non-normal status, issue status from the operator, normal status, normal delay status, and delay status from 3rd party. The undelivered category rate is influenced by the undelivered category, average delay status, not delay status, and long delay status. The delivered category is influenced by normal delay status, normal status, delay status from 3rd party, not normal status, issue status from the operator, very normal status, long delay status, not delay status, and average delay status. The delay from 3rd party may be influenced by non-normal status, issue status from the operator, normal status, normal delay status, average delay status, not delay status, and long delay status. The details of the division between parent and child nodes are shown in Table 2.

Table 2 Parent and Child nodes

Parents	Child	Parents	Child
undelivered_cat	rate_undelivered_cat	long_delay	delivered_cat
day_cat	undelivered_cat		rate_undelivered_cat
not_delay	delivered_cat		very_normal
	rate_undelivered_cat		maybe_delay_dr_from_3rd party
	very_normal	maybe_delay_dr_from_3rd party	delivered_cat
	maybe_delay_dr_from_3rd party		avg_noti_per_minute_cat
very_normal	delivered_cat		very_normal
unknown_summary	undelivered_cat	normal	delivered_cat
	very_normal		undelivered_cat
normal_delay	delivered_cat		avg_noti_per_minute_cat
	undelivered_cat		very_normal
	avg_noti_per_minute_cat		maybe_delay_dr_from_3rd party
	very_normal	not_normal	very_normal
	maybe_delay_dr_from_3rd party		maybe_delay_dr_from_3rd party
average_delay	delivered_cat		delivered_cat
	rate_undelivered_cat		undelivered_cat
	very_normal		avg_noti_per_minute_cat
	maybe_delay_dr_from_3rd party		very_normal
maybe_issue_from_operator	delivered_cat		maybe_delay_dr_from_3rd party
	undelivered_cat		
	avg_noti_per_minute_cat		

Based on Table 2, most of all parent nodes are influenced by the delivered category variable except the day category and undelivered category. Many parent nodes are affected by the undelivered category; the parent nodes are day category, unknown summary status, normal delay status, normal status, possible issue from operator status, and not normal status. The maybe delay from 3rd party variable affects several parent nodes, such as not delay status, unknown summary status, normal delay status, long delay status, normal status, average delay status, maybe issue from operator status, and not normal status. The undelivered category determines transactions in the morning/evening. The delivery status is very normal, only known by the delivered category variable. Normal delivery status is only influenced by the variables delivered category, undelivered category, average notification per minute category, very normal status, and maybe delayed from 3rd party status. The undelivered category variable influences the unknown summary status, and the status is very normal.

3.3.1 Conditional Probability Distributions (CPDs)

Conditional Probability Distribution is an analysis to help determine the probability value of each variable that has causality between each other or the probability of occurrence of one variable.

Table 3 CPDs value in the delivered category variable

Variable	Status	Variable delivered_cat	Probability
average_delay	**No**		
long_delay	No	Very Low	93.48%
maybe_delay_dr_3rd_party	No	Low	3.62%
maybe_issue_from_operator	No	Moderate	1.45%
normal	No	High	0.72%
normal_delay	No	Very High	0.72%
not_delay	No		
not_normal	No		
very_normal	No		

Table 4 CPDs value in the undelivered category variable

Variable	Status							
day_cat	Night	Night	Night	Night	Day	Day	Day	Day
maybe_issue_from_operator	No	No	No	Yes	No	No	No	Yes
normal	No	No	No	No	No	No	No	No
normal_delay	No	No	No	No	No	No	No	No
not_normal	No	No	Yes	No	No	No	Yes	No
unknown_summary	No	Yes	No	No	No	Yes	No	No
Variable undelivered_cat	**Probability**							
Low	98.93%	95.65%	0.21%	12.05%	98.62%	97.30%	0.78%	3.59%
High	1.07%	4.35%	99.79%	87.95%	1.38%	2.70%	99.22%	96.41%

Table 5 CPDs value in the Average Notification per Minute category variable

Variable	Status				
maybe_delay_dr_3rd_party	No	No	No	No	Yes
maybe_issue_from_operator	No	No	No	Yes	No
normal	No	No	Yes	No	No
normal_delay	No	No	No	No	No
not_normal	No	Yes	No	No	No
Variable avg_noti_per_minute_cat	**Probability**				
Low	93.48%	0.05%	0.01%	0.14%	0.00%
Moderate	6.44%	0.15%	24.07%	99.17%	96.56%
High	0.08%	99.80%	75.92%	0.69%	3.43%

Table 6 CPDs value in the Rate Undelivered category variable

Variable	Status					
average_delay	No	No	No	No	Yes	Yes
long_delay	No	No	No	Yes	No	No
not_delay	No	No	Yes	No	No	No
undelivered_cat	Low	High	Low	Low	Low	High
Variable rate_undelivered_cat	**Probability**					
Low	91.50%	5.18%	7.32%	9.05%	5.48%	28.57%
High	8.50%	94.82%	92.68%	90.95%	94.52%	71.43%

Table 7 CPDs value in the Maybe Delay From 3rd Party category variable

Variable	Status						
average_delay	No	No	No	No	No	No	Yes
long_delay	No	No	No	No	No	Yes	No
maybe_issue_from_operator	No	No	No	No	Yes	No	No
normal	No	No	No	Yes	No	No	No
normal_delay	No	No	Yes	No	No	No	No
not_delay	No	Yes	No	No	No	No	No
not_normal	Yes	No	No	No	No	No	No
Variable maybe_delay_dr_3rd_party	**Probability**						
No	99.95%	99.97%	99.25%	99.99%	99.86%	99.84%	98.72%
Yes	0.05%	0.03%	0.75%	0.01%	0.14%	0.16%	1.28%

Table 8 CPDs values in the Normal and similar category variables

Variable not_normal	Probability
No	96.23%
Yes	3.77%

Variable long_delay	Probability
No	98.77%
Yes	1.23%

Variable normal_delay	Probability
No	99.75%
Yes	0.25%

Variable normal	Probability
No	74.15%
Yes	25.85%

Variable average_delay	Probability
No	99.85%
Yes	0.15%

Table 9 CPDs value in uncertainty summary status categorical variable

Variable unknown_summary	Probability
No	99.76%
Yes	0.24%

Variable maybe_issue_ from_operator	Probability
No	98.61%
Yes	1.39%

When the variables are average delay, long delay, maybe a delay from a third party, maybe a problem from the operator, normal, normal delay, not a delay, not normal, the probability of very normal is obtained, the highest category is delivered, namely very low with a value of 93.48%.

The causality that occurs in the undelivered category variable is when the day category variable is evening, then possible problems from the operator, normal, normal delay, abnormal, and summary unknown with status no, then we get a low non-delivery category of 98.93% probability that it will occur; When the categorical variable day is night, then it may be issued from the operator, normal, normal delay, and abnormal with the status no, but the summary variable is unknown with the status yes, then the category obtained is low undeliverable with a 95.65% probability that will occur; When the categorical variable day is evening, then it may be issued from the operator, normal, normal delay, and unknown summary with the status no, but the variable is abnormal with the status yes, then the category obtained is not sent high with a 99.79% probability that will occur;When the possible categorical variables are removed from the operator, normal, normal delay, abnormal, and unknown summary with the status no, but the day variable with the status morning, then the low non-delivery category is obtained with a 98.62% probability that it will occur; When the day variable is morning, then possibly a problem from the operator, normal, normal delay, abnormal with status no, then summary unknown with status yes, then we get a low non-delivery category of 97.30% probability that will occur; When the day variable is morning, then it may be issued from the operator, normal, normal delay, unknown summary with status no, then abnormal with status yes, then a high non-delivery category is obtained with a 99.22% probability that will occur; When the day variable is morning, then abnormal, normal, normal delay, unknown summary with the status no, then possibly issuing a form operator with the status yes, then the high non-delivery category is obtained with a 96.41% probability that will occur.

The causality that occurs in the category variable average notifications per minute is when the categorical variable may be a third party delay, possibly a problem from the operator, normal, normal delay, abnormal with no status, then the low category is obtained in the average notification variable per minute of 93.48% probability that it will occur; When the categorical variable may be a third party delay, possibly a problem from the operator, normal, normal delay with status no, then abnormal with status yes, then the high category obtained in the variable average notification per minute is 99.80% likely to occur; When the category variable may be 3rd party delays, normal delays, abnormal, normal with the status no, then possibly issued from the operator with the status yes, then the medium category is obtained for the average notification variable per minute of 99.17% probability that will occur; When the category variable may be a problem from the operator, normal delay, abnormal, normal with the status no, then perhaps a third party delay with the status yes, then the medium category is obtained for the average notification variable per minute of 96.56% probability that it will occur.

The causality that occurs in the undelivered rate category variable is when the categorical variable is average delay, long delay, not delay with no status, then undelivered is low, then we get a low category in the undelivered rate variable with a probability that this will happen is 91.50%; When the category variable is average delay, long delay, not delay with no status, then high undelivered, then we get a high category in the undelivered rate variable with a probability that this will happen is 94.82%; When the variable category is average delay, long delay with the status no, then low undelivered, and not delay with the status yes, then we get a high category in the undelivered rate variable with a probability that this will happen is 92.68%; When the variable category is average delay, not delay with the status no, then low undelivered, and long delay with the status yes, then we get a low category in the undelivered rate variable with a probability that this will happen is 90.95%; When the variable category is long delay, not delay with the status no, then low undelivered, and average with the status yes, then we get a low category in the undelivered rate variable with a probability of that happening being 94.52%.

Sending an OTP message with the possibility of being categorized as not in the normal variable is likely to occur at 96.23%. Sending an OTP message with the possibility of being categorized as not in the unknown summary variable is likely to occur at 99.76%. Sending OTP messages with the possibility of being categorized as not in the average delay variable will occur at 99.85%. Sending OTP messages with the possibility of being categorized as not being in the maybe issue from the operator variable will occur at 98.61%.

The causality that occurs in the category variable maybe delay from 3rd party is when the variable average delay, long delay, maybe issue from operator, normal, normal delay, not delay with the status no, then not normal with the status yes, then the probability value of being categorized as no in the maybe delay from 3rd party variable is 99.95%; When the variable average delay, long delay, maybe issue from operator, normal, normal delay, not normal with status no, then not delay with status yes, then the probability value of being categorized as no in the variable maybe delay from 3rd party is 99.97%; When the variable average delay, long delay, maybe issue from operator, normal, not delay, not normal with the status no, then normal delay with the status yes, then the probability value of being categorized as no in the maybe delay from 3rd party variable is 99.25%; When the variable average delay, long delay, maybe issue from operator, normal delay, not delay, not normal with status no, then normal with status yes, then the probability value of being categorized as not in the maybe delay from 3rd party variable is 99.99%; When the variable average delay, normal, maybe issue from operator, normal delay, not delay, not normal with status no, then long delay with status yes, then the probability value of being categorized as not in the maybe delay from 3rd party variable is 99.86%; When the variable long delay, normal, maybe issue from operator, normal delay, not delay, not normal with the status no, then average delay with the status yes, then the probability value of being categorized as no in the maybe delay from 3rd party variable is 98.72%.

Table 10 Bayesian Network Evaluation

Evaluation/Variable	Day Category	Delivered Category	Undelivered Category	Rate Undelivered Category	Very Normal Status	Not Delay Status	Normal Status
Precision	54.23%	36.37%	84.36%	92.73%	99.95%	94.21%	74.06%
Recall	100%	37.91%	91.88%	89.82%	99.99%	100.00%	100.00%
F1-Score	70.32%	37.10%	86.98%	91.04%	99.97%	97.02%	85.10%
Accuracy	54.23%	35.37%	89.77%	92.20%	99.98%	94.21%	74.06%

Evaluation/Variable	Normal Delay Status	Average Delay Status	Not Normal Status	Long Delay Status	Unknown Summary Status	Maybe Delay From 3rd Party Status	Maybe Issue From Operator Status
Precision	99.80%	99.87%	96.33%	98.80%	99.75%	83.60%	98.61%
Recall	100.00%	100.00%	100.00%	100.00%	100.00%	82.73%	100.00%
F1-Score	99.90%	99.94%	98.13%	99.40%	99.88%	79.75%	99.30%
Accuracy	99.80%	99.87%	96.33%	98.80%	99.75%	79.77%	98.61%

Based on Table 10, It can be seen the accuracy obtained in predicting the future is more than 80%, namely Undelivered Category, Rate Undelivered Category, Very Normal Status, Not Delay Status, Normal Delay Status, Average Delay Status, Not Normal Status, Long Delay Status, Unknown Summary Status, and Maybe Issue From Operator Status.

Based on the explanation above, this means that the original hypothesis, namely maybe delay from 3rd party status causing irregularities in OTP SMS sending, does not have strong support, as evidenced by the accuracy value of only 79.77%, but rather from internal servers or more complex technical issues, such as the system's algorithm, which needs to be re-evaluated.

In terms of the evaluation matrix, the summary variable status shows that many variables in terms of Precision, F1-Score, and Accuracy have values greater than 85%, indicating that the results of this Bayesian network method can be used in business processes such as service evaluation and OTP message delivery.

4. CONCLUSIONS

From a meticulous examination of the extant data, it becomes palpably evident that the lion's share of transactions in the overarching commercial milieu predominantly transpires during the diurnal cycle. This phenomenon suggests a compelling proclivity for daytime transactional activities. Subsequent analysis reveals that the status categorizations most frequently associated with these transactions are the "Not Delay," "Very Normal," and "Unknown Summary" statuses, underscoring their centrality in this context.

The Bayesian network and a priori algorithm methods are helpful for viewing relationships between variables or causality, where both methods use probability. However, in testing the reliability method, the Bayesian network's overall average accuracy value was found to be better (14.5%) than the a priori algorithm using confidence values in predicting classification.

Delving deeper into the intricate nuances of the data, scholarly investigations and comprehensive research endeavors have painstakingly elucidated the symbiotic dynamics between parent nodes and their corresponding child nodes. It is found that parent nodes exert at least more than five discernible impacts on their subordinate entities. These multifaceted interactions span a range of categorizations: from the seemingly straightforward "Normal Delay," "Normal," and the somewhat ambiguous "Not Normal." It means the issue from existing data is caused by the firm providing the OTP service.

In the labyrinthine world of data analysis, precision is paramount. Intriguingly, the overarching summary status variables, which serve as pivotal benchmarks, predominantly exhibit commendably high precision values. However, it's crucial to note the outliers in this trend. Specifically, the "Normal Status" and the "Maybe Delay from 3rd Party Status" emerge as exceptions, bucking the prevalent trend of high accuracy. Augmenting the data's richness are the discoveries of "Undelivered Categories" and "Rate Undelivered Categories." Both of these categories not only add depth to the findings but also consistently boast elevated accuracy metrics, further cementing their significance in this comprehensive study.

The impact of obtaining fewer category statuses will undoubtedly make it easier to escalate issues for companies that provide OTP delivery services, thereby increasing the reputation of the services provided. Additionally, operational costs can be reduced in terms of issue escalation, both time and cost.

REFERENCES

[1] L. H. Lin, F. C. Lin, C. K. Lien, T. C. Yang, Y. K. Chuang, and Y. W. Hsu, "Electronic Payment Behaviors of Consumers under Digital Transformation in Finance—A Case Study of Third-Party Payments," *J. Risk Financ. Manag.*, vol. 16, no. 8, 2023, doi: 10.3390/jrfm16080346.

[2] Xendit, "e-Wallet Payments usage and trends in Indonesia," *Xendit*, 2022. .

[3] D. Permatasari, "Tantangan Cyber Security di Era Revolusi Industri 4.0," *Kementerian*

Keuangan Republik Indonesia, 2021. .
[4] Badan Siber dan Sandi Negara, “Lanskap Keamanan Siber Indonesia 2022,” Indonesia, 2022.
[5] L. E. Almeida, B. A. Fernández, D. Zambrano, A. I. Almachi, H. B. Pillajo, and S. G. Yoo, *A Complete One-Time Passwords (OTP) Solution Using Microservices: A Theoretical and Practical Approach*, no. September. Springer Nature Switzerland, 2023.
[6] M. H. S. Abousteit, A. F. Tammam, and A. M. Wahdan, “A novel approach for generating one-time password with secure distribution,” *Proc. World Conf. Smart Trends Syst. Secur. Sustain. WS4 2020*, pp. 461–466, 2020, doi: 10.1109/WorldS450073.2020.9210322.
[7] J. Díaz-Ramírez, “Machine Learning and Deep Learning,” *Ingeniare*, vol. 29, no. 2, pp. 182–183, 2021, doi: 10.4067/S0718-33052021000200180.
[8] . E. A. and . D. A., “Two Factor Authentication Framework Using OTP-SMS Based on Blockchain,” *Trans. Mach. Learn. Artif. Intell.*, vol. 7, no. 3, 2019, doi: 10.14738/tmlai.73.6524.
[9] U. Farooq, “Real Time Password Strength Analysis on a Web Application Using Multiple Machine Learning Approaches,” *Int. J. Eng. Res. Technol.*, vol. 9, no. 12, pp. 359–364, 2020, [Online]. Available: www.ijert.org.
[10] L. Pryor, J. Mallet, R. Dave, N. Seliya, M. Vanamala, and E. Sowells-Boone, “Evaluation of a User Authentication Schema Using Behavioral Biometrics and Machine Learning,” *Comput. Inf. Sci.*, vol. 15, no. 3, p. 1, 2022, doi: 10.5539/cis.v15n3p1.
[11] A. Ilahi and K. W. Axhausen, “Integrating Bayesian network and generalized raking for population synthesis in Greater Jakarta,” *Reg. Stud. Reg. Sci.*, vol. 6, no. 1, pp. 623–636, 2019, doi: 10.1080/21681376.2019.1687011.
[12] N. Luo, A. Nara, and K. Izumi, “An interaction-based bayesian network framework for surgical workflow segmentation,” *Int. J. Environ. Res. Public Health*, vol. 18, no. 12, 2021, doi: 10.3390/ijerph18126401.
[13] T. Lu, L. Wang, and X. Zhao, “Review of Anomaly Detection Algorithms for Data Streams,” *Appl. Sci.*, vol. 13, no. 10, 2023, doi: 10.3390/app13106353.
[14] G. Briganti, M. Scutari, and R. J. Mcnally, “A tutorial on Bayesian Networks for psychopathology researchers). Network theory comes with,” *COS (Center Open Sci.*, 2013.
[15] L. Vojković, A. K. Skelin, D. Mohovic, and D. Zec, “The development of a bayesian network framework with model validation for maritime accident risk factor assessment,” *Appl. Sci.*, vol. 11, no. 22, 2021, doi: 10.3390/app112210866.
[16] N. L. Ackerman, C. E. Freer, and D. M. Roy, “On the computability of conditional probability,” *J. ACM*, vol. 66, no. 3, 2019, doi: 10.1145/3321699.
[17] S. C. Bilqisth and K. Mustofa, “Determination of Temporal Association Rules Pattern Using Apriori Algorithm,” *IJCCS (Indonesian J. Comput. Cybern. Syst.*, vol. 14, no. 2, p. 159, 2020, doi: 10.22146/ijccs.51747.
[18] A. Y. Alin, K. Kusrini, and K. A. Yuana, “The Effect of Data Augmentation in Deep Learning with Drone Object Detection,” *IJCCS (Indonesian J. Comput. Cybern. Syst.*, vol. 17, no. 3, p. 237, 2023, doi: 10.22146/ijccs.84785.
[19] C. A. Bahri and L. H. Suadaa, “Aspect-Based Sentiment Analysis in Bromo Tengger Semeru National Park Indonesia Based on Google Maps User Reviews,” *IJCCS (Indonesian J. Comput. Cybern. Syst.*, vol. 17, no. 1, p. 79, 2023, doi: 10.22146/ijccs.77354.
[20] A. Thaljaoui, S. El Khediri, E. Benmohamed, A. Alabdulatif, and A. Alourani, “Integrated Bayesian and association-rules methods for autonomously orienting COVID-19 patients,” *Med. Biol. Eng. Comput.*, vol. 60, no. 12, pp. 3475–3496, 2022, doi: 10.1007/s11517-022-02677-y.
[21] D. Ersel and S. Günay, “Bayesian Networks and Association Analysis in Knowledge Discovery Process,” *İstatistikçiler Derg.*, vol. 5, pp. 51–64, 2012.