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Markov Chain Method to Predict The Sustainability of *E-Money* Use by Young People in Yogyakarta

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Abstract: The rapid development of digital technology has significantly driven the widespread adoption of electronic money (*e-money*), particularly among young adults who are generally more adaptive to technological innovations in payment systems. This study aims to predict the sustainability of *e-money* usage using a Markov chain model approach. Primary data was obtained through a survey of 100 respondents aged 17-30 years, who described their preferences for three *e-money* services: Dana, Mobile Banking, and ShopeePay. The analysis results show that Mobile Banking has the highest retention rate (62%) and is likely to be the dominant service in the long run. The steady-state prediction indicates that 57.48% of users will continue to use Mobile Banking, while Dana and ShopeePay decline to 19.01% and 23.51% respectively. Although *e-money* usage is still high, there is a tendency for preference shifts as well as a potential decline in sustainability. Therefore, digital service providers need to respond to this dynamic with innovative strategies to maintain the engagement of young users. This research contributes both theoretically through the application of mathematical models in digital consumer behaviour, and practically for the development of technology-based financial business strategies.

Keywords: *E-money, Youth, Markov Chain, User Preference, Continued Use, Mobile Banking, Consumer Behaviour Prediction*

Introduction

The development of digital technology has had a significant impact on various aspects of life, one of which is the payment system. In Indonesia, the digitalization of the financial system continues to grow rapidly, marked by the emergence of various innovations such as internet banking, credit cards, and electronic money services (*e-money).* The internet, which was initially only used as a means of disseminating information, has now evolved into a digital financial transaction platform (Adhika et al., 2019). This transformation has also changed people's consumption patterns and financial behavior, especially the younger generation who are more open to technological changes.

However, with the accelerating growth, it is important to predict the sustainability of the use of digital payment systems. This prediction is necessary to understand whether the application of digital payment technology will last a long time or will only be a temporary trend. In addition, sustainability predictions are essential for predicting various risks, such as digital access inequality, the security of user data, and the potential for financial dependency due to easy transactions. Understanding the factors that affect sustainability also allows the preparation of more strategies to produce services that are safer and can adapt to the needs of users in the future.

Although there are many studies on the prediction of *e-money* use, most studies focus on the more general scope of research such as factors that influence users' decision to move to other services, ease of transactions, benefits and advantages of digital products. There are still few researchers who have specifically discussed the sustainability aspect of the use of *e-money* in the long term, especially in the context of young people in Yogyakarta who transact a lot using *e-money* with all its convenience offers.

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Thus, the payment system using *e-money* among young people has also not been explored in depth in the framework of sustainability predictions.

One of the most prominent forms of digital payment system innovation is *e-money* in the form of digital wallets (e-wallets). E-wallets allow users to store funds and make transactions using only mobile devices. This service is designed to provide convenience, speed, and convenience in transacting, both *online* and *offline* (Abednego et al., 2023). The combination of mobile lifestyle and increased internet penetration has made young people the fastest group to adopt this digital payment system.

Data from Bank Indonesia shows that the use of *e-money* in the public has increased significantly from year to year. During the period from January to July 2020, the value of electronic money transactions was recorded at IDR 16.7 trillion, an increase of around 59% compared to the same period in the previous year of IDR 9.9 trillion. The highest increase occurred in April 2020, in line with the implementation of the Large-Scale Social Restrictions (PSBB) policy due to the COVID-19 pandemic, which encouraged people to take advantage of digital transaction services from home. In addition, a report from Iprice.co.id shows an increase in the use of financial applications by 70% in the period from June 2019 to June 2020. In June 2020 alone, there was an increase in application usage sessions by 2.83%. These facts show that *e-money* has become part of people's financial lives, especially the younger generation (Riska & Rachma, 2021).

However, the increase in use is not a guarantee that this behavior will continue consistently in the future. Changes in technology preferences, the emergence of new platforms, or reduced incentives such as promotions and *cashback* can affect the sustainability of e-money use . Therefore, a predictive analysis is needed to understand the extent to which the behavior of using *e-money* will persist, especially among young Indonesians.

This study uses the Markov Chain model strengthened by *the Technology Acceptance Model* (TAM) to analyze the sustainability of e-money use among young people in Yogyakarta. This approach was chosen for two main reasons. First, the Markov Chain is able to model the probability of transitions between usage states (such as active to passive, remain active, or stop using) quantitatively (Suryanto & Haryono, 2021). Second, TAM is needed to understand the psychological factors underlying the transition, especially perceived *usefulness* and *perceived ease of use* as the main determinants of technology adoption (Firdaus & Santoso, 2020). This model allows predicting changes in the status of a variable over time based on the transition patterns observed in the past. Markov chains are widely used in the fields of management, marketing, sales forecasting, and consumer behavior analysis due to their ability to model dynamic systems. In the context of this study, Markov chains were used to predict the transition of *e-money* usage status by young people, such as moving from active to passive users, staying active, or stopping using.

This study will specifically analyze several key variables such as *e-money* usage status (active, passive, no longer using), transaction frequency, and preference for the type of e-wallet service. In addition, the study also considers the factors that drive and inhibit the sustainability of use, such as the ease of access, promotion, and digital habits of young people aged 17–30 years as the target population.

With this approach, it is hoped that the research can make practical contributions to digital financial service providers in formulating sustainability and retention strategies for young users, as well as scientific contributions in developing probabilistic-based consumer behavior prediction models in the field of digital economy.

Literature Review

Markov Chains

Markov Chains are a very effective stochastic method for modeling dynamic systems in which the probability of transitions between states depends only on the current state (memoryless property), not on previous history. This technique is particularly suitable for predicting future distribution in the context of the adoption of technologies such as e-money for three main reasons:

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1. Capture transition behavior by modeling user movement between states (e.g. from non-user to active user or inactive user) through a transition probability matrix. This approach is more appropriate than time-series analysis that focuses on temporal trends or logistic regression that only predicts binary outcomes without considering the dynamics of the gradual transition (Nawi et al., 2020).
2. Suitability for discrete and categorical data such as frequency of use per month, where the Markov Chain is superior to time-series methods that require continuous data or logistical regression that is less flexible in handling sequential chain events (Aziz et al., 2021).
3. Its ability to make long-term predictions through steady-state probability calculations to estimate the stable distribution of e-money users, something that time-series analysis or logistical regression limited to single-point predictions does not possess (Kumar & Sharma, 2022).

When compared to other methods, the Markov Chain shows significant advantages. Time-series analysis is suitable for data with seasonal patterns or trends, but it is less effective in capturing user behavior that depends on current circumstances, such as the decision to stop using e-money that may depend on the previous month's experience (Hyndman & Athanasopoulos, 2018). Meanwhile, logistic regression, while useful for identifying determinants of adoption, has limitations in modeling multi-state transition processes such as those that can be done by the Markov Chain (Hair et al., 2022).

Several recent studies have proven the effectiveness of this method, such as the study by Nawi et al. (2020) that showed the accuracy of the Markov Chain in predicting the movement of fintech users, the research of Aziz et al. (2021) that compared the advantages of Markov with logistics regression, and the work of Kumar and Sharma (2022) who applied the steady-state of Markov to project the loyalty of e-money users in emerging markets.

Menurut Markov (dalam Dwijanto 2008:87) Model Rantai Markov yakni:

"For each time t, when the occurrence is K_t and all previous events are $K_{t(j)}$, ..., $K_{t(j-n)}$ that occurs from a known process, the probability of all future events $K_{t(j)}$ just depends on the occurrence $K_{t(j-1)}$ and does not depend on previous events, namely $K_{t(j-2)}$, $K_{t(j-3)}$,..., $K_{t(j-n)}$.

The description of the Markov chain is then outlined in Figure 1 where the movements of several variables in the future can be predicted based on the movements of these variables in the past. K_{t4} Influenced by events K_{t3}, K_{t3} Influenced by events K_{t2} And so on where this change occurs because of the role of *transition probability*. Event K_{t2} for example, it will not affect the occurrence K_{t4}.

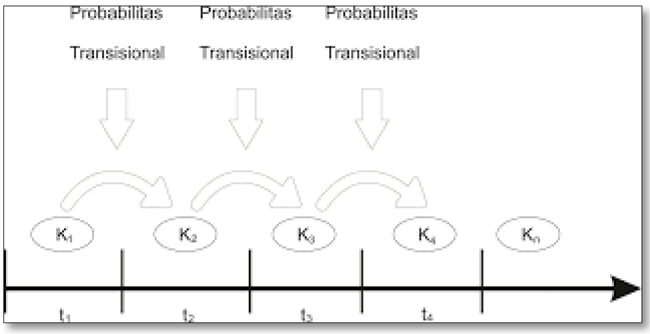

Figure 1, Events in the Markov Chain (Dwijanto 2008:87)

The above events are in chain. Therefore, this theory is known as the Markov Chain. Thus, the Markov Chain will explain the movements of some variables in a period of time in the future based on the movements of those variables in the present.

Chance of occurrence $K_{t(j)}$ expressed in vector form so that the sum of all the cells will always be 100%. Mathematically writeable:

$K_{t(j)} = P \times K_{t(j-1)}$

$K_{t(j)}$ = chance of occurrence on t(j)

P = Transitional Probability
t(j) = time to-j

Markov chains are one of the stochastic processes that are widely used to model process systems in the business world using mathematical techniques. This technique is used to estimate future changes by taking into account past changes in these variables (Abednego et al., 2023). Some of the conditions and of the Markov Chain are as follows:

1. The transition chance is equal to 1 in the initial condition of the system.
2. The condition is independent at all times.
3. Constant transition opportunities all the time.
4. This opportunity applies to all existing participants.

The states in the markov chain have different properties, some of the state properties in the markov chain are as follows:

1. *State Absorbing*
   This state can be expressed where the odds of a going to a are 1 or can be expressed by P(a,a) = 1
2. *State Transient*
   If the Markov chain starts from y, does not necessarily (uncertainly) return to y, then a state is called transient.
3. *State Recurrent*
   A state is called *recurrent* if a Markov chain starting with y will inevitably return to y at a finite time. If y *state absorbing*, then y is a *recurrent state*. However, it does not necessarily apply to the other way around.

Peluang Transisi Markov Chains

Suppose there is a Markov chain $\{X_t, t = 0,1,2,\ldots\}$ with state space $\{0,1,\ldots,M\}$. The chance of the system being in *state* i at a given time and moving to state j at the next time is denoted by P_{ij} (Howard & Rorres, 2004). This is called *one-step transition probability*, which describes the probability of moving from state i to state j in a single step of time.

If a system is in state i and has a chance to move to state j after n transition steps, then this opportunity is called *n-step transition probability* (Hiller and Liberman, 2008). Mathematically, the odds are expressed as:

$$P_{ij}^{(n)} = P\,(X_{n=j} \mid X_{0=i}), \quad \text{To } i,j \in \{0,1,2,\ldots\}$$

Value $P_{ij}^{(n)}$ indicates the probability that the process that was originally in state I will be in state j after n transition steps.

Transition opportunities in the Markov chain have two main properties:

1. Non-negatif: Transition opportunities are always of non-negative value, i.e.:
   $P_{ij} \geq 0$, To $i,j \in \{0,1,2,\ldots\}$
2. Total Probability: The number of chances of transitioning from a state i to all possible states is 1, which can be expressed as:
   $\sum_{j=0}^{\infty} P_{ij} = 1$, for all $i \in \{0,1,2,...\}$

These properties ensure that the Markov chain fulfills the basic principle of probability, where each transition has a well-defined chance and the total transition chance of a state is always worth 1.

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The n step *transition opportunity* can be calculated by multiplying the one-step transition opportunity matrix by *n* times. If *P* is a one-step transition opportunity matrix, then the transition opportunity matrix *n* step, $P^{(n)}$, can be obtained by: $P^{(n)} = P^n$

This approach allows for long-term predictions about system behavior, such as an analysis of the use of *e-money* by the younger generation in this study. By understanding transition opportunities, we can model the likelihood of moving from one state (e.g., low *e-money* usage rates) to another state (e.g., high e-money usage rates) over a given period of time.

Discrete Markov Chain Transition Opportunity Matrix

A Markov process with *a state space* consisting of *countable* numbers is called a discrete Markov chain. The time index on this Markov chain is expressed as $T = \{0,1,2,\ldots\}$, whereas state spaces are represented as a set of non-negative integers $\{0,1,2,\ldots\}$. Notasi $X_n = i$ shows that the process is in state *i* at the *n time* (Howard, 1984).

The formal form of the transition opportunity matrix on a discrete Markov chain is expressed as follows:

$$P(X_{t+1} = j \mid X_t = i) = P(X_t = j \mid X_0 = i)$$

If this equation applies to every $t = 0,1,2,\ldots n$, then the one-step transition opportunity is said to be stationary and denoted by P_{ij}. *n* step **transition opportunity**, which is denoted by $P_{ij}^{(n)}$, expresses the probability that the process started at the iii will be in *state j* after *n* steps. Because $P_{ij}^{(n)}$ is a conditional opportunity, so the following conditions must be met:

$$0 \leq P_{ij}^{(n)} \leq 1 \text{ for all } i \text{ and } j.$$

A matrix that shows all nnn-step transition opportunities, called n-step transition opportunity matrix, is expressed as:

$$\mathbf{P} = \begin{bmatrix} P_{1,1} & P_{1,2} & \ldots & P_{1,j} & \ldots & P_{1,S} \\ P_{2,1} & P_{2,2} & \ldots & P_{2,j} & \ldots & P_{2,S} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ P_{i,1} & P_{i,2} & \ldots & P_{i,j} & \ldots & P_{i,S} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ P_{S,1} & P_{S,2} & \ldots & P_{S,j} & \ldots & P_{S,S} \end{bmatrix}.$$

Source: P2K STEKOM. (n.d.). *Matriks stokastik*. P2K STEKOM.

Methodology

This study uses primary data collected through surveys to obtain information about changes in user preferences in choosing *e-money* applications. The survey was conducted by distributing an online questionnaire using Google forms, and was equipped with several observations to strengthen the research results. In this survey, 100 young respondents in Yogyakarta were involved. This amount is considered adequate for the initial study, given the limited time and resources available. The researcher asked questions related to the change in reference in using the e-money application, this study also used *purposive sampling* techniques or targeted samples. This technique was chosen because the researcher determined respondents based on certain criteria that were considered relevant and appropriate, this study focused on young people 17 to 30 years old. This shows that the data obtained can describe the conditions or views of the target group in a more in-depth and directed manner. as well as analyzing the factors that affect the shift of user interest in choosing *certain e-money* services .

Research results

This article analyzes the prediction of the sustainability of the use of *e-money* services in Yogyakarta using the Markov Chain approach. From the results of the questionnaire aimed at 100 respondents, the data as shown in table 1 were obtained.

Table 1. Services, number of respondents, and number of percentages. This table shows the number of users of each *e-money service* in the initial year of the study (year 0).

No	Service	Number Of Respondents (People)	Percentage (%)
1	Dana	37	37%
2	Mobile Banking	36	36%
3	Shopeepay	27	27%
Jumlah		100	100%

To understand how user preferences change from one year to the next, an analysis was performed using a probability transition matrix.

Moving in Choosing a Service

Tabel 2. Current Number of Service Users

No	Service	Current Amount	Dana	Mobile Banking	Shopeepay
1	Dana	37	24%	37%	39%
2	Mobile Banking	36	19%	62%	19%
3	Shopeepay	27	15%	63%	22%

In the initial year (0-th year), the probability transition matrix is given as follows:

$$P0 = \begin{bmatrix} 0,24 & 0,37 & 0,39 \\ 0,19 & 0,62 & 0,19 \\ 0,15 & 0,63 & 0,22 \end{bmatrix}$$

In the early stages, data showed that out of 100 respondents, the most used e-Money services were Dana (37%), followed by Mobile Banking (36%), and ShopeePay (27%). This distribution became the basis for the analysis of user transitions in the following years using the Markov Chain method.

To calculate the distribution of users in the 2-nd year, a two-fold transition matrix is multiplied, namely: $P(2)=P(0)\times P(0)$

In the second year (2-nd year), the probability transition matrix is given as follows:

$$P\,(2) = \begin{bmatrix} 0,24 & 0,37 & 0,39 \\ 0,19 & 0,62 & 0,19 \\ 0,15 & 0,63 & 0,22 \end{bmatrix} 2 = \begin{bmatrix} 0,24 & 0,37 & 0,39 \\ 0,19 & 0,62 & 0,19 \\ 0,15 & 0,63 & 0,22 \end{bmatrix} X \begin{bmatrix} 0,24 & 0,37 & 0,39 \\ 0,19 & 0,62 & 0,19 \\ 0,15 & 0,63 & 0,22 \end{bmatrix}$$

$$= \begin{bmatrix} 0,1864 & 0,5639 & 0,2497 \\ 0,1919 & 0,5744 & 0,2337 \\ 0,1887 & 0,5847 & 0,2266 \end{bmatrix}$$

Furthermore, the distribution of e-money service users in the 2nd year was obtained by multiplying this matrix by the initial distribution of users (number of respondents).

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$$P\ (2) = \begin{bmatrix} 0{,}1864 & 0{,}5639 & 0{,}2497 \\ 0{,}1919 & 0{,}5744 & 0{,}2337 \\ 0{,}1887 & 0{,}5847 & 0{,}2266 \end{bmatrix}$$

$$[\ 37\ \ 36\ \ 27]\ \mathrm{x} \begin{bmatrix} 0{,}1864 & 0{,}5639 & 0{,}2497 \\ 0{,}1919 & 0{,}5744 & 0{,}2337 \\ 0{,}1887 & 0{,}5847 & 0{,}2266 \end{bmatrix}$$

Result:
[18,90 57,33 23,77]

This shows that in the second year (2-nd year), it can be predicted that around 19 people will continue to use or switch to Dana, around 59 people will continue to use Mobile Banking, and around 24 people will continue to use Shopeepay.

Long-Term Equilibrium Analysis (Steady State)

In long-term analysis, the system will achieve a steady-state state where the distribution of users remains stable over time.

Equilibrium state transition matrix (long-term):

$$[\pi_1\ \ \pi_2\ \ \pi_3] = [\pi_1\ \ \pi_2\ \ \pi_3]\ \mathrm{x} \begin{bmatrix} 0{,}24 & 0{,}37 & 0{,}39 \\ 0{,}19 & 0{,}62 & 0{,}19 \\ 0{,}15 & 0{,}63 & 0{,}22 \end{bmatrix}$$

$\pi = [\pi_{1,} \pi_{2,} \pi_3]$
$\pi_1 = 0{,}24\pi_1 + 0{,}19\pi_2 + 0{,}15\pi_3$
$\pi_2 = 0{,}37\pi_1 + 0{,}62\pi_2 + 0{,}63\pi_3$
$\pi_3 = 0{,}39\pi_1 + 0{,}19\pi_2 + 0{,}22\pi_3$

Persamaan pertama:
$\Pi_1 = 0{,}19\pi_2 – 0{,}15\pi_3 = 0$
$\Pi_1 = 0{,}19\pi_2 + 0{,}15\pi_3$

Persamaan kedua:
$– 0{,}37\pi_1 + \pi_2 – 0{,}63\pi_3 = 0$
$– 0{,}37(0{,}19\pi_2 + 0{,}15\pi_3) – 0{,}63\pi_3 = 0$
$– 0{,}7\pi_2 + 0{,}55\pi_3 + \pi_2 – 0{,}63\pi_3 = 0$
$– 0{,}93\pi_2 – 0{,}685\pi_3 = 0$
$\pi_2 = 0{,}685\pi_3 \div 0.93$
$\pi_2 = 0{,}736\ \pi_3$

Subtitusi:
$\pi_1 + \pi_2 + \pi_3 = 1$
$(0{,}19\pi_2 + 0{,}15\pi_3) + \pi_2 + \pi_3 = 1$
$0{,}19\ (0{,}736\ \pi_3) + 0{,}15\ \pi_3 + 0{,}736\ \pi_3 = 1$
$0{,}14 + 0{,}15\ \pi_3 + 0{,}15\ \pi_3 + 0{,}736\ \pi_3 + \pi_3 = 1$
$1{,}026\ \pi_3 = 1$
$\pi_3 = 0{,}2351$

$\pi_2 = 0{,}736 \times 0{,}2351$
$= 0{,}5748$

$\pi_1 = 0{,}19\ \pi_2 + \mathrm{o}{,}15\ \pi_3$
$= 0{,}19\ (0{,}5748) + 0{,}15\ (0{,}2351)$
$= 0{,}1092 + 0{,}0353$
$= 0{,}1901$

With the substitution and elimination technique, the following results were obtained:

π_1 = 0,1901

π_2 = 0,5748

π_3 = 0,2351

$$P^n = \begin{bmatrix} 0,1901 & 0,5748 & 0,2351 \\ 0,1901 & 0,5748 & 0,2351 \\ 0,1901 & 0,5748 & 0,2351 \end{bmatrix}$$

Predict the number of *long-term* e-money service users:

$$[37 \quad 36 \quad 27] \times \begin{bmatrix} 0,1901 & 0,5748 & 0,2351 \\ 0,1901 & 0,5748 & 0,2351 \\ 0,1901 & 0,5748 & 0,2351 \end{bmatrix}$$

= [19,01 57,48 23,51]

These results suggest that the system will tend to be in the π2 (Mobile Banking) state more often than the other two states (π_1 and π_3).

Markov Chain's analysis shows that the preference of young people in Yogyakarta to use *e-money* is changing. At the beginning of the study, Dana was used by 37% of respondents, Mobile Banking 36%, and ShopeePay 27%. However, the results of the calculation show that Mobile Banking has the highest retention rate of 62%, with many users switching to Mobile Banking at 37% and 63%, respectively.

The prediction of the distribution of users in the second year shows an increase in Mobile Banking to 57.33%, while Dana and ShopeePay decreased by 18.90% and 23.77%, respectively. Steady-State's analysis predicts that Mobile Banking will dominate with 57.48% of users, with Dana only 19.01% and ShopeePay only 23.51%.

Discussion

Table 2 shows the change in user preferences from year 0 to the next year in the form of a probability transition matrix. Probability transition matrix. This matrix uses the possibility that a user remains on the same service or moves to another service.

From the second table it can be deduced.

- Dana users have a 24% probability of staying on Dana, 37% switching to Mobile banking, and 39% switching to Shopeepay.
- Mobile Banking users have a 19% probability of staying in Dana, 62% staying in Mobile Banking, and 19% switching to Shopeepay
- Shopeepay users have a 15% probability of staying on Shopeepay, 63% moving to Mobile Banking, and 22% staying on Shopeepay

To predict the distribution of users in the 2-nd year, multiplying the transition matrix by the initial distribution (P(0)) is performed. The results of the calculation are as follows:

P(2)=P(0)× matriks transisi

Known initial distribution of users:

P(0)= [37,36,27]

After multiplying by the probability transition matrix, it is obtained:

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*P(**2**)= [18,90 57,33 23,77]*

It can be concluded that in the 2nd year

- About 19 people remain using or switching to Dana
- Around 59 people continue to use Mobile Banking
- Around 24 people continue to use Shopeepay

From the analysis using the Markov Chain method, there was a change in the distribution of e-money service users in two years. It can be seen that Mobile Banking is becoming an increasingly used service with the percentage of users increasing to 59% of the total population. On the other hand, the number of Dana and Shopeepay users has decreased.

This shows that in a certain period of time, Mobile Banking has a certain appeal that has a stronger appeal than other users. Factors such as ease of transactions, full features, or promotions from banks could be the main reasons for this shift in preferences.

Conclusion

This study analyzes the sustainability of *e-money* use by young people in Yogyakarta by utilizing the Markov Chain model as a predictive approach. Based on survey data that has been collected from 100 young respondents, it is known that in the early stages there are 59% active users, 26% passive, and 15% who stop using *e-money*. Using the Markov Chain model, it was found that over the next two years, the proportion of active users is predicted to decrease to 54.9%, while passive users increase to 29.5%, and those who stop to 15.6%.

This transition shows that although *e-money* is still quite dominant among young people, there is a tendency to slow down in the sustainability of use. Factors such as changing preferences, lack of service innovation, as well as potential technological saturation can be the cause of this transition. Therefore, *e-money* service providers need to continue to innovate and maintain user engagement through increased convenience, security, and loyalty programs that are relevant to the needs of young people to predict the sustainability of *e-money* use.

Theoretically, this research contributes to the use of probabilistic mathematical models to predict consumer behavior in the digital era. Meanwhile, practically, the results of this prediction can be used as a basis for digital finance industry players to formulate user retention strategies so that the use of *e-money* remains sustainable in the future.

Reference

Abednego, S., et al. (2023). Perpindahan Minat Mahasiswa Terhadap Penggunaan Aplikasi E-Wallet Sebelum dan Setelah Perkuliahan Luring di Masa Pandemi Covid. *Math journal*. Volume 8 No. 1, Desember 2022 - Mei 2023.

Adhika, B, N., & Endah, M, R. (2019). Landscape E-Money di Indonesia. Konferensi Nasional Ilmu Administrasi.

Aziz, S., Rahman, M. H., & Latif, R. (2021). Comparative analysis of Markov chains and logistic regression in predicting mobile wallet adoption. *International Journal of Information Management, 59*, 102345.

Dwijanto. (2008). *Riset operasi*. Semarang: Universitas Negeri Semarang.

Firdaus, A., & Santoso, B. (2020). Penerapan Technology Acceptance Model (TAM) dalam analisis penerimaan sistem pembayaran digital. *Jurnal Ilmu Komputer dan Bisnis, 11*(2), 45–60.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2022). *Multivariate data analysis* (8th ed.).

Hiller, F. S., & Liberman, G. J. (2008). *Operations Research: An Introduction*. Pearson Education.

Howard, R., & Rorres, C. (2004). *Introduction to Probability Models*. Academic Press.

Kumar, R., & Sharma, P. (2022). Steady-state analysis of e-money usage via Markov chains: Evidence from emerging markets. *Technological Forecasting and Social Change, 175*, 121356.

Nawi, N. C., Ahmad, A., & Zainal, A. (2020). Markov chain model for predicting user behavior in digital payment systems. *Journal of Financial Technology, 8*(2), 45–60.

Nurlela, S., Fanani, A., & Khaulasari, H. (2023). Prediksi harga minyak mentah WTI menggunakan metode Fuzzy Time Series Markov Chain. Jurnal Fourier, 12(1), 10–19.

Riska, W, A., & Rachma, I. (2021). Pengaruh Penggunaan Uang Elektronik (E-Money) Berbasis Server Sebagai Alat Transaksi Terhadap Penciptaan Gerakan Less Cash Society Pada Generasi Milenial Di Surabaya. *Jurnal Ekonomika dan Bisnis Islam,* Volume 4 Nomor 1, E-ISSN: 2686-620X Halaman 196-206

Suryanto, T., & Haryono, N. (2021). Aplikasi rantai Markov dalam prediksi perilaku konsumen finansial digital. *Jurnal Statistika Terapan*, *17*(1), 33–48.

Hia, Elisabet Desy Yulianawati, and Marlina Setia Sinaga. "Implementation of Markov Chain on MSME Data for QRIS Users in Medan City." *Asian Journal of Community Services*, vol. 1, no. 4, 2022, pp. 148–151.

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