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MODELLING STUDENTS' ACADEMIC PERFORMANCE AND PROGRESS: A DISCRETE-TIME MARKOV CHAIN APPROACH

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ABSTRACT

Predicting students' performance has become increasingly challenging due to the large volume of data in educational databases. Academic achievement reflects learning effectiveness and serves as a key indicator of teaching quality, institutional standards, and overall student development. Higher education systems operate hierarchically, with students progressing through academic levels annually or exiting as graduates or dropouts. Understanding and evaluating student progression is vital amidst evolving educational dynamics. This study models students' academic performance and progression using a discrete-time Markov chain approach to predict future outcomes. Data on students' enrollment and performance for five(5) sessions were collected from the Department of Statistics, Federal University of Technology, Minna. The Markov chain model was constructed for different academic levels and their absorbing states. Key metrics, including expected time spent at each level, absorption probabilities, and graduation or withdrawal likelihoods, were estimated. The findings show that 100-level entrants have an 80.5% chance of graduating and a 19.5% risk of withdrawal, with graduation likelihoods increasing with progression—reaching 99.4% at 500-level. The forecasts from the constructed Markov chain models showed that 100-level entrants are 99.4% likely to graduate after five sessions, 200-level entrants after three sessions, and 300-level entrants after one session. The study shows that while attrition rates are higher in the early stages, students advancing beyond the 200-level exhibit strong prospects for completion. These findings underscore the university's effective programs and support systems, particularly in retaining and advancing students beyond the critical early stages.

Keywords: Academic Performance, Discrete-Time Markov Chain, Absorption Probability, Transient State, Absorbing State

INTRODUCTION

Student academic performance serves as a measure of learning effectiveness and is often used to evaluate both individual student development and the overall quality of teaching in higher education. It functions as an indicator of educational outcomes, helping educators explore strategies that enhance learning and promote academic achievement in vocational institutions.

In the study of Zheng & Mustappha (2022), they said schoolwork, or academic work, is what is meant by academic. "School work" refers to the learning tasks assigned by the school and is separated into phases, whereas "academic work" refers to the objectives reached by students as a result of the accumulation of learning. Performance is the result of a test in a particular subject or the full course; achievement, on the other hand, is the degree to which a student can reach after completing a term of study or training (Lamas, 2015). Academic performance is thought to be equal to academic achievement. According to Zheng & Mustappha (2022) in their study, said the credit point average, or GPA, of college students is a generally used indicator of their academic success and can be accurately calculated from their course grades (Zheng & Mustappha, 2022). However, a number of scholars have put forth various definitions of academic performance since they feel that grades are synonymous with achievement (Brookhart *et al.*, 2016). According to Astin (2014) academic success encompasses behavioral, psychological, and non-cognitive outcomes in addition to cognitive ones and also according to Bloom (1956) academic success entails the following: knowledge, skills, and proper actions. It also involves values and attitudes. Every educational system has to include an evaluation of pupils' development. All postsecondary educational establishments can be viewed as hierarchical structures, with each student residing in a particular study phase for a full academic year before either graduating or dropping out. The challenge of comprehending and evaluating pupils' progress within the educational system is crucial because of ongoing changes and an increase in data (Mashat *et al.*, 2012).

Markov chain models have been widely applied in various contexts to analyze progression, retention, and forecasting in educational, demographic, and environmental studies. In higher education, several studies have utilized these models to track student performance and transitions across academic levels. Dalvi (2023), Olu (2020), and Brezavšček *et al.* (2017) demonstrated high graduation probabilities and declining withdrawal rates as students advanced through academic levels, while Muhammad *et al.* (2019) and Adeleke *et al.* (2014) emphasized improved academic performance and retention over time. Similar findings by Kibiya *et al.* (2020) highlighted the importance of early intervention to address higher withdrawal rates in initial years. In secondary education, Egbo *et al.* (2018) and Auwalu *et al.* (2013) effectively modeled student progression and resource management, aligning with the broader trend of using Markov chains for enrollment forecasting and reducing wastage. Beyond education, Azizah *et al.* (2019)) utilized Markov models to forecast rainfall patterns, and Nkemnole & Ikegwu (2022) explored population growth strategies in Nigeria, identifying the impact of extended birth gaps and contraceptive use. Studies such as Hlavatý & Dömeová (2014) and Otieno & Oyala (2020) further illustrated the versatility of Markov models in evaluating exam outcomes and academic career development. These applications underscore the utility of Markov chains in understanding dynamic processes and informing policy and strategic decision-making across various fields.

MATERIALS AND METHODS

Materials

A combination of software tools was employed for data preparation, statistical analysis, and modeling. For the initial stage, Microsoft Excel 2016 were used to organize the raw data. The data were arranged and sorted by academic levels, and additional columns were included to classify students' performance statuses. After the data preparation in Excel, the dataset was imported into Python 3 through Jupyter Notebook with the ipykernel environment. Python were used for detailed analysis, including tracking students' performance at each level and monitoring their progression to the next level. The students' IDs serves as unique identifiers to determine whether each student progresses, graduates, or withdraws.

Method

Discrete-Time Markov Chain Model

Discrete Markov Regardless of the past, the future state of a sequential process that depends only on the current state is predicted and analyzed using chain modeling, a potent mathematical framework. A wide range of industries, including economics, engineering, biology, and education, have adopted this modeling method. (Ross, 2014). Discrete Markov The foundation of chain modeling is the idea of a Markov chain, which is a stochastic process that changes states depending on predetermined transition probabilities. (Norris, 1998). The Memoryless property state that the current state is the only factor that determines the future state; the preceding series of events is not relevant. The Memoryless Property is that; $P(X_{n+1} = j|X_n = i_n, X_{n-1} = i_{n-1}, ..., X_0 = i_0) = P(X_{n+1} = j|X_n = i)$, where X_n is a series of random variables having discrete time intervals between $t_0, t_1, ..., t_n$, there must be a countable or finite collection of states in the operation.

Basic Discrete-Time Markov Chain Model

A probability distribution controls each transition as the process moves through discrete time steps in a discrete-time Markov chain. The transition probability matrices are the general form of a discrete-time or state transition matrix of an absorbing state with "a" absorbing and "t" transient states, utilizing the (Grinstead & Snell, 2012) notations is given by;

$$P_{ij} = \begin{bmatrix} Q & A \\ 0 & I \end{bmatrix} \quad (1a)$$

Where each of the element in the matrix in equation (1a) are the canonical form for the Transition Probability matrix and; Q = t x t matrix showing the transition probability between the transient states. A= t x a (non-zero) matrix representing the transition probability from the transient states to the absorbing states, 0 = a x t (Zero-matrix) showing the transition probability from the absorbing states to the transient states and I = a x a matrix showing the transition probability between the absorbing states, it is an identity matrix.

The transition probability matrix [TPM] (P_{ij})

$$P_{ij} = \begin{matrix} \\ 100L \\ 200L \\ 300L \\ 400L \\ 500L \\ W \\ G \end{matrix} \begin{bmatrix} 100L & 200L & 300L & 400L & 500L & W & G \\ 0 & \pi_{12} & 0 & 0 & 0 & 0 & 0 \\ 0 & \pi_{22} & \pi_{23} & 0 & 0 & \pi_{2W} & 0 \\ 0 & 0 & \pi_{33} & \pi_{34} & 0 & \pi_{3W} & 0 \\ 0 & 0 & 0 & \pi_{44} & \pi_{45} & \pi_{4W} & 0 \\ 0 & 0 & 0 & 0 & \pi_{55} & \pi_{5W} & \pi_{5G} \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (1b)$$

Where π_{22}, π_{33}, π_{44}, and π_{55} are the probabilities that the students repeated 200, 300, 400 and 500 level respectively, π_{12}, π_{23}, π_{34} and π_{34} are the probabilities that the students promoted to the next level from 100 to 200, 200 to 300, 300 to 400 and 400 to 500 level respectively, π_{2w}, π_{3w}, π_{4w} and π_{5w} are the probabilities that the students are been withdrawn at 200, 300, 400 and 500 level respectively and π_{5G} is the probability that students graduated at 500 level.

Fundamental matrix

It is used to analyze the Markov Chain's behavior. Each entry represents the expected number of times the chain is in each transient state. It is typically denoted by N and is computed as

$$F_{txt} = [I_{txt} - Q_{txt}]^{-1} \quad (2)$$

Where I in equation (2) is totally different from the one in equation (1a), the identity matrix I in equation (1a) is a matrix with dimension (a x a) , where a is absorbing state while the Identity matrix I in equation (2) is a matrix of (t x t) dimension, where t mean the transient state and Q is the (t x t) transition matrix for the transient states. (Hlavatý & Dömeová, 2014). If f_{ij} are the entries for the fundamental matrix F_{txt} then f_{ij} is given by

$$\begin{cases} \frac{1}{1-P_{ii}}, i = j \\ \frac{\prod_{a=1}^{i-1} P_{aa+1}}{\prod_{a=1}^{i} (1-P_{aa+1})} \\ 0, otherwise \end{cases} \quad (3)$$

The expected steps before the absorbing state/time to absorption

This is the average number of steps it takes for the system to reach an absorbing state starting from any initial state. For each of the transient state, the number of steps taken can be represented by the ith entry of the column vector E in (3)

$$E_{tx1} = F_{txt} C_{tx1} \quad (4)$$

Where F is the (t x t) fundamental matrix and C is a column vector of dimension (t x t) with one (1) as its entries.

The probabilities of absorption

This is the likelihood that the chain or system will reach the absorbing state. Given that the process began in the transitory state i, let B have the entries b_{ij} (where b_{ij} is the chance of being absorbed in absorbing state j). B is a (t x a) matrix, and it may be obtained by

$$B_{txa} = F_{txt} A_{txa} \quad (5)$$

Data Source and Description

The data for the thesis is a secondary type of data, which is the records for undergraduate students enrolled into Statistics Department Federal University of Technology, Minna during the five consecutive years and their progress for the five years of their program. These records include information such as the student ID numbers, academic levels, enrollment status (enrolled, graduate, Withdrawn) and demographic information (Gender, Date of birth, State of Origin and Local Government Area). The defined states and transition probabilities based on the university's academic structure are; Transient states (100 level to 500 level) and Absorbing states (Withdrawal, Graduation). The assumptions to be adopted based on the rule guiding the progress of students of Federal university of technology, Minna according to the Student handbook, 2019-2024 session; Students who are currently in 100 level can only progress to the 200 level, cannot be repeated nor withdrawn, students who are currently in 200 level to 400 level can either progress to the next level, repeated same level or been withdrawn, students who are currently in 500 level can either graduate, repeat or withdraw and the students who has been withdrawn can never graduate and the graduated ones cannot re-enrolled the same programme which has just been successful finished.

States transition diagram

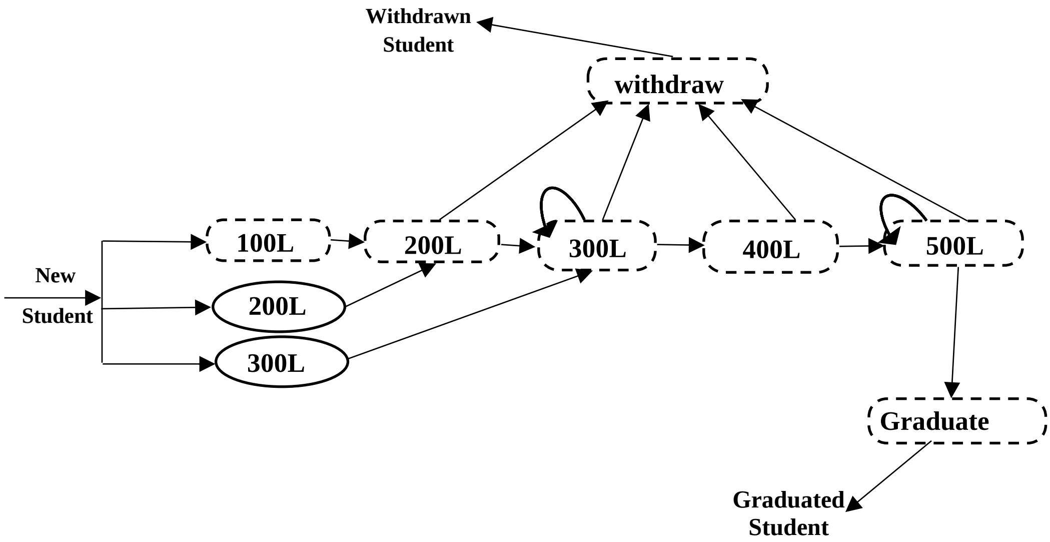

Figure 1: Transition Diagram

Figure (1) is the summary Markov chain that describes the 5 transient and 2 absorbing states for the all the students in Federal University of Technology, Minna irrespective level that were enrolled.

RESULTS AND DISCUSSION

The Summary of Student Enrolled and their Progress

Table 1: The Summary of Progression for all the Student Enrolled into Statistics Department for the Five Sessions Under Study

	100 LEVEL	200 LEVEL	300 LEVEL	400 LEVEL	500 LEVEL
PROMOTED	469	507	418	409	354
REPEATED	0	0	57	0	53
WITHDRAW	0	54	38	9	2
TOTAL	**469**	**561**	**513**	**418**	**409**

States Transition Probabilities Matrix

To develop a one-step transition probabilities matrix, equation (1) which shows the summary matrix for the students is first derived from table (1) and each row element is divided by its row totals to obtain the one-step transition probability matrix in equation (2)

$$n_{ij} = \begin{array}{c} \\ 100L \\ 200L \\ 300L \\ 400L \\ 500L \\ W \\ G \end{array} \begin{bmatrix} 100L & 200L & 300L & 400L & 500L & W & G \\ 0 & 469 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 507 & 0 & 0 & 54 & 0 \\ 0 & 0 & 57 & 418 & 0 & 38 & 0 \\ 0 & 0 & 0 & 0 & 409 & 9 & 0 \\ 0 & 0 & 0 & 0 & 53 & 2 & 354 \\ 0 & 0 & 0 & 0 & 0 & 103 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 354 \end{bmatrix} \quad (6)$$

Transition probabilities matrix P_{ij} **estimate**

Equation (7) shows the probabilities of transitioning between the different states.

$$P_{ij} = \begin{array}{c} \\ 100L \\ 200L \\ 300L \\ 400L \\ 500L \\ W \\ G \end{array} \begin{bmatrix} 100L & 200L & 300L & 400L & 500L & W & G \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.904 & 0 & 0 & 0.096 & 0 \\ 0 & 0 & 0.111 & 0.815 & 0 & 0.074 & 0 \\ 0 & 0 & 0 & 0 & 0.978 & 0.022 & 0 \\ 0 & 0 & 0 & 0 & 0.130 & 0.005 & 0.866 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (7)$$

The canonical form for TPM estimate

The canonical form for the Transition Probabilities Matrix in equation (7) is given as the matrices in equation (8), (9), (10) and (11)

Equation (8) shows the probabilities of transitioning within the transient state. That is, the probability that a student will remain in the transient state.

$$Q = \begin{array}{c} \\ 100L \\ 200L \\ 300L \\ 400L \\ 500L \end{array} \begin{bmatrix} 100L & 200L & 300L & 400L & 500L \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0.904 & 0 & 0 \\ 0 & 0 & 0.111 & 0.815 & 0 \\ 0 & 0 & 0 & 0 & 0.978 \\ 0 & 0 & 0 & 0 & 0.130 \end{bmatrix} \quad (8)$$

Equation (8) shows that, the probability that a 100 level student returns as a 100 level student after the long vacation is 0%, he/she has 100% chance of returning as a 200 level student, 0% chance of returning as a 300 level, 400, and 500 level student. Also, the probability that a 200 level student returns as a 100 level student is 0%, he/she has 90.4% chance of returning as a 300 level student and 0% chance of returning as 200, 400 and 500 level students and same as others.

Equation (9) shows the transition probabilities matrix from the transient states to the absorbing states.

$$A = \begin{matrix} \\ 100L \\ 200L \\ 300L \\ 400L \\ 500L \end{matrix}\begin{bmatrix} W & G \\ 0 & 0 \\ 0.096 & 0 \\ 0.074 & 0 \\ 0.022 & 0 \\ 0.005 & 0.866 \end{bmatrix} \quad (9)$$

The transition probability matrix in equation (9) shows that, the probability of a student transitioning from 100 level to any of the absorbing state (withdraw, graduate) is 0%, there is 9.6%, 7.4%, 2.2% and 0.5% chance that a student in 200, 300, 400 and 500 level been withdrawn respectively. A student at 100, 200, 300 or 400 has 0% chance of been a graduate while a student at 500 level has 86.6% chance of being a graduate.

Equation (10) shows the transition probability from the absorbing states to the transient states.

$$0 = \begin{matrix} \\ W \\ G \end{matrix}\begin{bmatrix} 100L & 200L & 300L & 400L & 500L \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (10)$$

The transition probability matrix in equation (10) shows that a student who has been withdrawn or graduated from the programme has 0% chance of enrolling back for the same program.

Equation (11) shows the transition probabilities within the absorbing states.

$$I = \begin{matrix} \\ W \\ G \end{matrix}\begin{bmatrix} W & G \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (11)$$

The transition probability matrix in equation (11) shows that a student who has been withdrawn will remain 100% withdrawn and he/she has 0% of being a graduate and a graduate student will remain 100% a graduate from the programme and has 0% probability of being withdrawn.

Fundamental Matrix Estimate

$$F_{ij} = \begin{matrix} \\ 100L \\ 200L \\ 300L \\ 400L \\ 500L \end{matrix}\begin{bmatrix} 100L & 200L & 300L & 400L & 500L \\ 1 & 1 & 1.017 & 0.828 & 0.931 \\ 0 & 1 & 1.017 & 0.828 & 0.931 \\ 0 & 0 & 1.125 & 0.917 & 1.030 \\ 0 & 0 & 0 & 1 & 1.124 \\ 0 & 0 & 0 & 0 & 1.149 \end{bmatrix} \quad (12)$$

Estimate for the expected steps before the absorbing state (time to absorption)

$$E_{ij} = \begin{matrix} 100L \\ 200L \\ 300L \\ 400L \\ 500L \end{matrix}\begin{bmatrix} 4.776 \\ 3.776 \\ 3.072 \\ 2.124 \\ 1.149 \end{bmatrix} \quad (13)$$

A student starting in the 100 level (1st academic year) is expected to remain in the system for about 4.776 more sessions on an average before graduation. This number suggested that on an average, a student in 100 level has approximately 5 more sessions before he or she can graduate. A student starting in the 200 level (2nd academic year) is expected to remain in the system for about 3.776 more sessions on an average before graduation. This suggests that a 200level student is expected to progress close to four additional sessions, aligning with completing the remaining sessions in the program and potentially entering a phase of graduation and same as others.

Estimate for the probability of absorption (withdraw, graduation)

$$b_{ij} = \begin{matrix} \\ 100L \\ 200L \\ 300L \\ 400L \\ 500L \end{matrix}\begin{bmatrix} W & G \\ 0.194 & 0.806 \\ 0.194 & 0.806 \\ 0.108 & 0.892 \\ 0.027 & 0.973 \\ 0.006 & 0.994 \end{bmatrix} \quad (14)$$

Equation (14) shows that a student starting in the 100 level has 19.4% and 80.6% chance of being withdraw and graduate respectively from the university this simply means that a student who starts in 100 level is more likely to graduate (80.6%) than withdraw (19.4%) and 200level students have the same likelihood of withdrawal and graduation, showing that the risk of withdrawal doesn't change between the 100 and 200 levels. 300level students has its likelihood of graduating increases to 89.2%, while the probability of withdrawal decreases to 10.8%, indicating a stronger tendency to complete the program once a student reaches this level and this continue for other levels. The observed steady increase in retention rates of the students in this study as they advance through academic levels is consistent with the findings by Adam (2015) and Adeleke *et al.* (2014), both of whom reported a decline in withdrawal rates and improved academic performance at higher academic levels. Unlike Olu (2020), who included a vacating state to address classification errors, this work assumes a more straightforward structure. While this simplifies the modeling process, it might overlook certain nuances in student pathways, as evidenced by Mamudu (2017), who introduced hiatus states to account for temporary breaks in academic progression.

Predicting using the N-Step Transition Probabilities Matrices

Equation (2) is one-step, then (15), (16), (17) and (18) are the third to fifth steps given as:

Figure (15) shows the 2-step transition probability matrix (n= 2)

$$P_{ij}^2 = \begin{matrix} \\ 100L \\ 200L \\ 300L \\ 400L \\ 500L \\ W \\ G \end{matrix}\begin{bmatrix} 100L & 200L & 300L & 400L & 500L & W & G \\ 0 & 0 & 0.904 & 0 & 0 & 0.096 & 0 \\ 0 & 0 & 0.100 & 0.736 & 0 & 0.163 & 0 \\ 0 & 0 & 0.012 & 0.091 & 0.797 & 0.100 & 0 \\ 0 & 0 & 0 & 0 & 0.127 & 0.026 & 0.847 \\ 0 & 0 & 0 & 0 & 0.017 & 0.006 & 0.978 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (15)$$

Figure (16) shows the 3-Step Transition Probabilities Matrix (n =3)

$$P_{ij}^3 = \begin{matrix} \\ 1L \\ 2L \\ 3L \\ 4L \\ 5L \\ W \\ G \end{matrix}\begin{bmatrix} 1L & 2L & 3L & 4L & 5L & W & G \\ 0 & 0 & 0.100 & 0.736 & 0 & 0.163 & 0 \\ 0 & 0 & 0.011 & 0.082 & 0.721 & 0.186 & 0 \\ 0 & 0 & 0.001 & 0.010 & 0.192 & 0.107 & 0.690 \\ 0 & 0 & 0 & 0 & 0.016 & 0.027 & 0.957 \\ 0 & 0 & 0 & 0 & 0.002 & 0.006 & 0.992 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (16)$$

Figure (17) shows the 4-Step Transition Probabilities Matrix

$$P_{ij}^4 = \begin{array}{c} \\ 100L \\ 200L \\ 300L \\ 400L \\ 500L \\ W \\ G \end{array}\begin{bmatrix} 100L & 200L & 300L & 400L & 500L & W & G \\ 0 & 0 & 0.011 & 0.082 & 0.721 & 0.186 & 0 \\ 0 & 0 & 0.001 & 0.009 & 0.173 & 0.193 & 0.624 \\ 0 & 0 & 0.0002 & 0.001 & 0.035 & 0.108 & 0.856 \\ 0 & 0 & 0 & 0 & 0.002 & 0.027 & 0.971 \\ 0 & 0 & 0 & 0 & 0.0003 & 0.006 & 0.994 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (17)$$

Figure (18) shows 5-Step Transition Probabilities Matrix

$$P_{5Years} = \begin{array}{c} \\ 100L \\ 200L \\ 300L \\ 400L \\ 500L \\ W \\ G \end{array}\begin{bmatrix} 100L & 200L & 300L & 400L & 500L & W & G \\ 0 & 0. & 0.001 & 0.009 & 0.173 & 0.193 & 0.624 \\ 0 & 0 & 0.0001 & 0.001 & 0.031 & 0.194 & 0.774 \\ 0 & 0 & 0.00002 & 0.0001 & 0.006 & 0.108 & 0.886 \\ 0 & 0 & 0 & 0 & 0.0003 & 0.027 & 0.973 \\ 0 & 0 & 0 & 0 & 0.00004 & 0.006 & 0.994 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (18)$$

All departments in FUTMINNA expect or hope that most of the students enrolled into 100 level will graduate within five years. It is interesting to see that the model in equation (18) shows that after 5 years, a 100 level student at FUTMINNA has a 99.4% chance of graduating and 0.6% chance of being withdrawn.

The findings align closely with the findings of Olu (2020) and Muhammad *et al.* (2019), both of whom noted higher instability and withdrawal rates among first-year students. Similar to the results, Olu (2020) attributed this very low withdrawal rates to students' struggles with adapting to new academic environments and institutional frameworks. Similarly, Muhammad *et al.* (2019) observed an improvement in students' academic performance and reduced dropout rates as they advanced through academic levels, a trend consistent with our observations. Additionally, Dalvi (2023) and Kibiya *et al.* (2020) also reported that the probability of graduation increases significantly as students progress to higher levels, underscoring the importance of student retention strategies in the early years. In this study, the pattern is further corroborated, emphasizing the critical role of foundational support systems to mitigate early withdrawals. The emphasis on early intervention strategies to reduce withdrawals aligns with Kibiya *et al.* (2020) and Hlavatý & Dömeová (2014), both of whom identified critical points in students' academic journeys where targeted support could significantly improve outcomes. By identifying periods of instability, the results reinforce the importance of proactive measures in the first year of study, consistent with Olu (2020)s' recommendations. The findings from this study, like those of Egbo *et al.* (2018) and Otieno & Oyala (2020), provide valuable insights for institutional planning and policy development and by emphasizing the predictive capabilities of Markov models, it contributes to a growing body of evidence supporting their use in optimizing resource allocation and improving student outcomes.

CONCLUSION

The analysis of students' progression at the Federal University of Technology Minna over the past five academic sessions reveals key insights into the dynamics of academic performance and retention. The findings indicate that the early years of a student's academic journey are critical, with a significant risk of withdrawal, but those who progress beyond the 200 level have a markedly higher chance of completing their studies. This trend suggests a robust educational system that effectively supports students as they advance through their academic careers, with the most significant attrition occurring in the early stages. The higher retention and graduation rates in the later years reflect the effectiveness of the university's academic programs and student support systems at those levels.

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