

Student Retention and Enrollment Dynamics in Selected Nigerian Private Universities Utilizing a Markov Chain Approach

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Abstract: - Markov frameworks help address important problems in Universities because of the abundance of information these institutions collect for administration and admissions, as well as for documenting student enrollment. The current academic regulations at Covenant University (CU), Babcock University (BU), and Redeemer's University (RU) are flexible regarding the order in which students earn their degrees. This results in a range of enrollment sequences and an average period to the degree, as well as to enrollment and retention. This implies using a hidden Markov model with hidden states to identify academic bottlenecks and enhance admissions by grouping students into homogeneous classes. This provides a similar absorbing state for both undergraduate and postgraduate students, thereby optimizing student retention.

Key-Words: - Hidden Transition matrix; Probability; Universities; Hidden Class approach; Enrollment; Retention.

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1 Introduction

Throughout an academic career, students may change their enrollment status each session, whether undergraduate or postgraduate, [1], [2]. According to a 2023 survey of Nigerian universities, over 53% of students were undergraduates, while only 29% were postgraduates, [3]. Undergraduate college students often have higher transition and retention rates than postgraduate counterparts, [4]. Previous studies found that enrollment status has a significant influence on college perseverance [5], while course load substantially affects students' persistence and completion rates, [6]. First-semester students who enroll in more credit units are generally more likely to complete all programme requirements and graduate successfully, [6].

There is no universally accepted definition distinguishing undergraduate and postgraduate students beyond semester-based academic classification, [7]. Since many students transition between undergraduate and postgraduate enrolment during their academic journey, a simple binary classification is often inadequate, [8]. Mixed enrollment strategies have also been associated with improved student success because students

who combine different enrollment pathways are generally more likely to complete their degree programme, [9].

The classification of students based on higher-order enrollment and retention behaviour rather than current enrollment status has received increasing research attention, [10]. Similarly, differences between semester-based enrollment models and current enrollment status are often relatively small in explaining student retention, [11]. At Covenant University, Babcock University and Redeemer's University, approximately 35% of students proceed to postgraduate studies, while about 40% remain within undergraduate programmes, [12], [13]. However, enrollment during a single semester does not adequately represent the long-term enrollment and retention process that occurs throughout a student's academic career, [14].

This study therefore seeks to identify semester-by-semester enrollment and retention patterns using a dynamic Markov Chain approach. Specifically, the study applies a hidden Markov model to classify students according to their enrollment behaviour, particularly students who alternate

between undergraduate and postgraduate studies, and to examine graduation patterns and other academic outcomes.

2 Literature Review

In reality, not all college enrollment and retention efforts result in degree completion, such as a PhD, and a large proportion of students withdraw before graduation, resulting in a possible loss of time and financial resources, [15], [16]. Several factors influence student persistence, including demographic characteristics, academic engagement, and patterns of educational participation. These factors may be broadly classified into socioeconomic background, enrollment patterns, and academic participation. Providing additional financial support increases the likelihood of programme completion [17], while gender has also been identified as a significant factor contributing to differences in academic achievement, [18], [19], [20]. Academic trajectories demonstrate a significant relationship between degree completion and students' credit load, [21]. Likewise, continuous versus non-continuous enrollment and intermittent enrollment patterns influence students' persistence and graduation rates, with several studies reporting a positive relationship between continuous enrollment and successful degree completion, [22], [23], [24], [25]. Furthermore, retention rates and persistence improve as student enrollment increases, [26]. Collectively, these findings demonstrate that several factors contribute to differences in students' academic achievement. However, most previous studies classify students primarily according to their current enrollment status while overlooking enrollment sequences, transition behaviour, hidden states, and absorbing states that characterize students' long-term academic progression. Accordingly, this study applies a Hidden Transition Markov Chain model to optimize and model student enrollment throughout the academic journey by examining the sequence of enrollment transitions rather than relying solely on students' current enrollment status.

3 Methodology

o determine students' enrollment and retention approaches and to define the effect of enrollment and retention on students (i.e., postgraduate and undergraduate) in terms of an absorbing rate, the

study utilized a hidden transition Markov chain approach. In the context of modelling, the utilization of the Markov chain is not new. It has been applied to study decision-making and sequential processes, [27], [28]. For instance, Markov models have been used as monitoring tools to categorize observations and predict retention for each category, [27]. Similarly, the Markov chain model has been used to simulate the behaviours and activities of high school students, [29]. To evaluate variations in behaviour and achievement between groups, the authors clustered students based on their transition matrices, generating parameters for each student using the Baum–Welch algorithm (Figure 1, Appendix), which illustrates the dynamics of a system as it transitions between states. The system produces an outcome $y_{i|y_i}$ when it is in a particular state or mode of operation. In contrast to the conventional Markov approach, transitions are sometimes unobservable; therefore, they can only be inferred from a sequence of outputs. The observations in this study refer to the actual enrollment and retention status in any given period as documented in the students' profiles. The dynamic state corresponds to the student's enrollment, which in turn affects retention (i.e., undergraduate and postgraduate). The study starts with the following notations to provide a formal definition of the Markov model approach: the set of N alternative states for the system is represented by $R = \{R_1, R_2, \dots, R_N\}$, and $D = [d_{ij}]$. x_n is a transition in which each d_{ij} represents the likelihood that a given period will see a transition from state i to state j ; A sequence of observations of length p is represented by $y = y_1, y_2, \dots, y_p$, each chosen from the set of P possible observations. $z = z_1, z_2, \dots, z_n$, where β is the system's original distribution. The output y_t at period p is produced by a distinct probability density when the system is in state q_i ; the probability distribution is $Z = v_i$ (ot). There is a need to determine the optimal model parameters (y, z, r) that replicate known observations to develop a Markov chain approach to describe student enrollment and retention methods. A mathematical framework, such as the Baum-Welch approach, is a cyclic model that includes the distribution and likelihood (probability) of categorizing perceptions and deciphering connections between hidden constructs and perceptions. The decoding and probability calculations are updated iteratively.

4 Results and Discussions

This paper's investigation utilizes original, processed records of undergraduate and graduate students collected in 2023 from Covenant University, Babcock University, and Redeemer's University, three private universities in Nigeria. The dataset comprises approximately 455 student records and contains detailed institution-specific information on individual students across these universities. The dataset includes variables such as student retention, degrees awarded (bachelor's, master's, and Ph.D.), and courses undertaken at Covenant University, Babcock University, and Redeemer's University.

Table 1 (Appendix) presents the gender distribution across Covenant University (CU), Babcock University (BU), and Redeemer's University (RU). Of the 455 students, 207 are male and 248 are female, indicating a slight female majority across the three institutions. Covenant University has 210 students (99 males and 111 females), Babcock University has 201 students (87 males and 114 females), while Redeemer's University, the smallest institution in the sample, has 44 students (21 males and 23 females). The gender difference is most pronounced in Babcock University. The admission distribution shows that 41.8% of students are undergraduates, 49.1% are postgraduates, and 9.1% belong to other admission categories, indicating a substantial presence of transfer and non-traditional students. Enrollment patterns vary across semesters. During the first semester, postgraduate students constitute the majority (50.5%) compared with undergraduate students (43.5%). However, in the second semester, undergraduate enrollment increases to 54.6%, while postgraduate enrollment declines to 34.4%. These findings indicate variations in enrollment and retention dynamics between undergraduate and postgraduate students. Overall, the data reveal a consistent female majority, a considerable proportion of transfer students, and dynamic enrollment transitions between the first and second semesters. The analysis is based on observed student enrollment sequences within one academic year, covering both first- and second-semester enrollments and including first-year and transfer students.

4.1 Markov Chain Application

Let $z_{ij} = (z_{ij1}, \dots, z_{ijp}, \dots, z_{ijP})$ $1 \leq i \leq n$ $1 \leq j \leq J$ be the series of observed transition values for students iii ($i=1, \dots, n$) ($i =$

$1, \dots, n$) ($i=1, \dots, n$) and jjj ($j=1, \dots, J$) ($j = 1, \dots, J$) ($j=1, \dots, J$) in the context of discrete period ppp . This notation is utilized in the model equations. Furthermore, a discrete time-varying hidden construct, v_{ip} , is introduced to represent the unknown state of student iii at period ppp and to account for the hidden heterogeneity dynamics that vary with each phase. As a result, every student has a sequence of hidden transition states. Given this, $k_i = (k_{i1}, \dots, k_{ip}, \dots, k_{iP})$ $k_i = (k_{i1}, \dots, k_{ip}, \dots, k_{iP})$ $k_i = (k_{i1}, \dots, k_{ip}, \dots, k_{iP})$, whose observed manifestation is represented by the vectors z_{ij} z_{ij} z_{ij} for every path jjj . The variate Markov chain approach [30] is based on two presumptions. First, each state z_{ijp} z_{ijp} z_{ijp} for student i at period p is independent of $z_{i,p-1,j}, z_{i,p-2,j}, \dots, z_{i1,j}$ $z_{i,p-1,j}, z_{i,p-2,j}, \dots, z_{i1,j}$ $z_{i,p-1,j}, z_{i,p-2,j}, \dots, z_{i1,j}$ and of each z_{ipj} z_{ipj} z_{ipj} , where $j' \neq j$ $j' \neq j$ $j' \neq j$ given the transit state $X_{ip} = k_{ip}$ $X_{ip} = k_{ip}$ $X_{ip} = k_{ip}$ at period p . This is an independent state that is characterized as a class of hidden approach [31, 32], to which the Markov chain is a subset. Secondly, the hidden variable y_{ip} y_{ip} y_{ip} is a first-order Markov model with transition states $\{1, \dots, R\}$ $\{1, \dots, R\}$ $\{1, \dots, R\}$; that is, k_{ip} k_{ip} k_{ip} is independent of $k_{i,p-2}, k_{i,p-3}, \dots, k_{i1}$ $k_{i,p-2}, k_{i,p-3}, \dots, k_{i1}$ $k_{i,p-2}, k_{i,p-3}, \dots, k_{i1}$, given $k_{i,p-1}$ $k_{i,p-1}$ $k_{i,p-1}$. Stated differently, the two suppositions imply that the hidden process captures the relationship between transitions of the same student across different periods and that the hidden state at each given moment depends only on the hidden transition in the preceding period (Figure 1, Appendix).

$$\{z_{i11}, \dots, z_{i1j}, z_{i21}, \dots, z_{i2j}, \dots, z_{ip1}, \dots, z_{ipj}\}$$

$$k_{i1} \rightarrow k_{i2} \rightarrow \dots \rightarrow k_{ip}$$

The variate approach of the Markov chain

Based on the suppositions, the manifest likelihood of the observed succession of information is figured out as:

$$P\{z_{ij} = Z_{ij}\} = \sum_{k=1}^K \{p(z_{ij} | k_i = k_1)p(k_{i1} = k_1) \times \prod_{p=2}^P p(z_{ijp} | k_{ip} = k_p)p(k_{ip} = k_p | k_{i,p-1} = k_{p-1})\}$$

(1)

where the transition probability of moving from the hidden transition k_{p-1} to k_p is represented by $p(k_{ip} = k_p | k_{i,p-1} = k_{p-1})$, the initial probability of starting from the hidden transition is represented by $p(k_{i1} = k_1)$, and the conditional probability of the observed transition given the hidden phase is given by $p(z_{ijp} | k_{ip} = k_p)$ (period-homogeneity). Similar to hidden Markov, the autocorrelation observed in

repeated measures on the same student can be explained by the 1st-order, expressed by transition probabilities $p(kip = kp \mid ki, p-1 = kp-1)$, where the hidden transition at period p is based on the hidden transition at period $p-1$. Similar to the hidden Markov, the autocorrelation observed in repeated measures on the students can be explained by the first-order process in the context of a Markov Chain, represented by the transition $p(kip = kp \mid ki, p-1 = kp-1)$, where the hidden transition at period p depends only on the hidden phase at period $p-1$. Furthermore, the measurement error is explained by the relationship between concealed and observed transitions, as represented by the probabilities $p(zijp \mid kip = kp)$. The model is a generalization of a hidden Markov model that allows the study to account for heterogeneity in the population over time, in addition to measurement error, on the basis that students are composed of hidden transitions. Mathematically, the study introduces a hidden period variable mi with a discrete property D at $m1, \dots, md$ and related probabilities $\pi1 = p(mi = m1), \dots, \pi d = p(mi = md)$. Therefore, the transition is modeled in Equation (2):

$$P(zij = Zij) = \pi d [p(zij \mid ki = k, mi = md) p(ki = k)] \quad (2)$$

In contrast to the hidden transition state z , the probabilities in the multi-modal manner of the Markov chain are unique to the hidden category md . Furthermore, the probabilities $\pi1, \dots, \pi d$ are the same for each student, implying that these variables are dependent on a period constant in an associative pattern. Equation (2) substitutes the probability $\pi d = p(mi = md)$, denoted by xi as a vector of student variables, and x is an observed outcome. This new expression, $\pi d (xi) = p(zij \mid ki = k, xi = x)$, is explained using a log approach:

$$\log[\pi_d(x_i) / \pi_1(x_i)] = \beta_{0d} + x_i^T \beta_d, \quad d = 2, \dots, D \quad (3)$$

Typically, the Markov chain is determined by optimizing the log-likelihood function $\beta = zij$ with the definition of $p(zij = zij)$ given in Equations (1) and (2). It takes an optimization technique, such as the Expected-Maximization model, to optimize the log function. The R language of the hidden Markov chain has functions that optimally carry out the maximization. Here, it is important to note that the study recommends repeating the procedure with random output to avoid the issue of lower boundary

maxima. The choice of d of hidden categories can be motivated by practical considerations, i.e. hidden transitions, or based on the model's information, utilizing a non-parametric approach.

4.1.1 Markov Chain in a Hidden Transition State

Equation (1) estimates a Markov chain with 2 hidden states and 2 hidden transitions. According to the preceding section's explanation, the evaluated probabilities of the two states correspond to 1 and 0, respectively; this implies that $i = 1, \dots, d$, $p(z_{i1}) = 1$ and $p(z_{i1} = 2) = 0$. Furthermore, the evaluated probabilities in a transition state is outlined in the matrix and demonstrate a considerable persistence within the concealed states.

$p(z_{i1} = 1 \mid z_{i,p-1} = 1)$	$p(z_{i1} = 2 \mid z_{i,p-1} = 1)$
$p(z_{i1} = 1 \mid z_{i,p-1} = 2)$	$p(z_{i1} = 2 \mid z_{i,p-1} = 2)$
$p(z_{i1} = 1 \mid z_{i,p-1} = 1)$	$p(z_{i1} = 2 \mid z_{i,p-1} = 1)$

0.00	0.40	0.60
0.18	0.71	0.11
0.20	0.40	0.40

Any student enrolled in a degree or a postgraduate course at the start of the follow-up period falls into state 1, and subsequently moves into state 2. While the transition from state to state i.e. 1-2 expresses linearity, and the evaluated probability at any given time point is 60%, the regression from state 2 to 1 is not achievable ($p(z_{i1} = 1 \mid z_{i,p-1} = 2) = 0$). The evaluated probabilities, which show the likelihood of enrolling at a given period in a transition hidden state, are the most intriguing part of the hidden Markov. The larger the inclination not to enroll j , the lower $p(z_{i1} = 1 \mid kip)$. From a mathematical point of view, the anticipated probability for enrollment is close to 1, as these are required. As a result, the study anticipates that students will adhere to the chronological order in their study plan for the first-year exams. The assumed hidden transition matrix for each school is (0.35, 0.45, and 0.20). For first-year enrollment, the optimum scenario correlates to probabilities in the range of: $0.35 \leq p(kip \mid zip = zp) \leq 1.000$, with 1.00 and 0.35 being the outcomes of 1s in the first academic year's enrollment and retention sequences. The probabilities relate to the lower enrollment rate planned for the second academic year, where $0.45 \leq p(kip \mid zip = zp) \leq 0.610$, and for the third-year exam probabilities: $0.20 \leq p(kip \mid zip = zp) \leq 0.310$. In fact, transition probabilities are lower than the lower boundary mentioned above due to the study's

enrollment rate (0.35 in year 1). Table 2 (Appendix) displays the output of the enrollment transition probabilities.

Table 2 (Appendix) presents transition probabilities for hidden states 1 and 2 indicate that state 2 is consistently higher, reflecting higher enrollment than in state 1. This aligns with the initial and transition estimates. Enrollment odds in state 2 are generally high, notably 68% in Babcock University. In contrast, state 1 shows lower probabilities: 32%, while Covenant University records 49% and 51%, respectively. Redeemer's University shows slightly lower dynamics, transitioning from 42% to 58%.

4.2 Concomitant Factors Model

The regression variable in the logic-optimal approach specified by equation (3) is presented in Table 3 (Appendix), showing p and t coefficients and the error function. Table 4 (Appendix) reports concomitant function values for each transition class, clarifying baseline characteristics and supporting interpretation. Significant distinctions exist between classes 2-5 and class 1, attributed to enrollment. Class 1 represents the transition state to classes 2-5, the absorbing state, with an estimated enrollment rate of 80.1%. Table 4 (Appendix) shows a minimum of 41.1% in class 1, while other classes range from 21.3% to 56.82%, with class 4 highest. Similarly, class 1 records the highest value (80.1%), while class 4 has the lowest (43.4%), followed by class 5 (51.01%). Regarding the interpolation, category (class) 5 shows a significant change (Table 3, Appendix), which is related to enrollment and students (undergraduate and postgraduate). Class 5 does, in fact, have a notably higher enrollment (51.2% compared to 41.1% in class 1). Hidden classes 1 through 5 differentiate students' enrollment, whether undergraduate or postgraduate, in universities, as shown in Table 4 (Appendix), which compares each hidden class's descriptive statistics with those of the overall outcome.

5 Conclusions

From the perspective of undergraduate and postgraduate admissions, the study looked at student retention and enrollment trends. The study developed and implemented a hidden Markov transition technique on data sets from Covenant University, Babcock University, and Redeemer's University to categorize students into undergraduate and postgraduate groups. Students in classes 4 and 5 exhibit minimal enrollment, leading

to low retention, whereas class 1 shows a high probability based on the sequence plan and absorbing state. In line with this, class 1 students enroll at a higher rate than class 4. The outcomes help guide university guidance services.

The study makes two contributions it introduces a hidden transition Markov approach for classification based on multi-class dynamics in the probability of enrollment and retention, unlike traditional models that classify enrollment integrally. Secondly, numerical evaluation highlights students' vulnerability, urging colleges to recognize them early and create platforms that retain them.

6 Recommendations

Universities such as Covenant University, Babcock University, and Redeemer's University should adopt data-driven monitoring systems, such as hidden Markov transition models, to identify students in low-enrollment and low-retention categories (e.g., classes 4 and 5) and provide targeted academic and support interventions to improve their retention outcomes.

University guidance and support services should prioritize early identification of vulnerable students and establish structured support platforms (e.g., mentoring, academic advising, and engagement programs) to enhance enrollment continuity and reduce dropout risks.

Institutions should regularly monitor enrollment transition patterns between undergraduate and postgraduate programmes. Understanding these transition dynamics will enable universities to improve admission planning, resource allocation, and long-term student retention strategies.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Oni Gabriel: conceptualization; Ogunnaike Olaleke: methodology, Oludugba Adebayo: software, Oni Gabriel: writing-original draft preparation; Ogbari Mercy: review and editing.

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APPENDIX

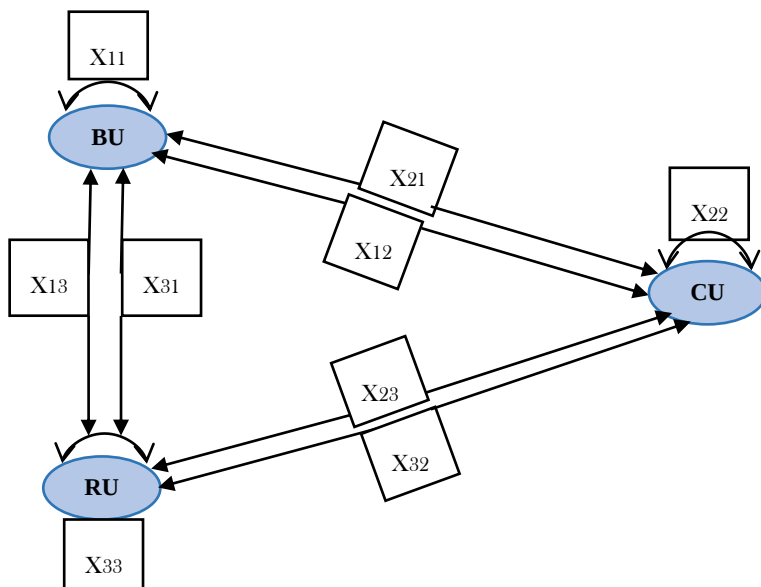


Fig. 1: Transition dynamics
Source: created by the authors

Table 1. Distribution of Respondents for Male and Female

Gender	Covenant University (CU)	Babcock University (BU)	Redeemer's University (RU)	Total
Male	99	87	21	207
Female	111	114	23	248
Total	210	201	44	455

Admission Distribution

Percentage	Undergraduate	Postgraduate	Total
	41.8%	49.1%	100%

Enrollment and retention rate

	Undergraduate	Postgraduate	Total
First Semester	43.5%	50.5%	100%
Second Semester (M.Phil / Ph.D)	54.6%	34.4%	100%

Source: Authors' field survey (2023).

Table 2. Transition probabilities output from the Markov chain Approach utilizing a hidden transition model

School	Transition hidden ratio	Probabilities
Covenant University (CU)	Transition State One Transition State Two	0.49 0.51
Babcock University (BU)	Transition State One Transition State Two	0.32 0.68
Redeemer's University (RU)	Transition State One Transition State Two	0.42 0.58

Source: created by the authors

Table 3. Logic optimal approach for hidden class: Estimated coefficients with error function, t, and p-outcomes

	Evaluation	Error function	t- outcome	p-outcome
Hidden class 2(intercept), Student, enrollment	2.151 0.213	0.711 0.511	1.103 0.128	0.011 0.641
Hidden class 3(intercept), Student, enrollment	2.542 0.124	1.400 0.615	1.681 0.520	0.081 0.710
Hidden class 4(intercept), Student, enrollment	5.682 0.434	1.388 0.401	4.101 -1.1810	0.000 0.291
Hidden class 5(intercept), Student, enrollment	5.101 0.910	1.361 0.311	3.711 -2.311	0.004 0.1011

Source: created by the authors

Table 4. Appropriation of concomitant (corresponding) student factors

Variable (Factor)	Category (class) one	Category (class) two	Category (class) three	Category (class) four	Category (class) five	All categories (class)
Students: Undergraduate and postgraduate	0.801 0.411	0.477 0.510	0.214 0.512	0.311 0.611	0.512 0.410	0.510 0.420
University (CU,BU, RU)	0.512	0.614	0.319	0.310	0.218	0.401

Source: created by the authors