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Modelling Technological Changes, and Student Switching Behaviour of Selected Private University Students in a Developing Economy

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Abstract

This study examines the influence of technological changes on student loyalty and switching behaviour in selected private universities in Southwest Nigeria, where differences in technological infrastructure and students' adaptability to technological innovations complicate the prediction of student loyalty and retention. The study aims to model and analyse the influence of technological changes on student switching behaviour and loyalty using Markov Chain analysis and to provide quantitative evidence that university administrators can apply to improve student retention and institutional competitiveness. A quantitative research design was adopted, and data were collected through structured questionnaires administered to 464 final-year students from three selected private universities in Southwest Nigeria. A total of 455 valid responses were analysed using Markov Chain transition probability matrices to model students' loyalty and postgraduate enrolment decisions under different technological conditions. The findings indicate that improvements in internet facilities, online library support services, laboratory equipment, and overall technological infrastructure increase the probability of students remaining loyal to their institutions. For instance, improved internet facilities increased the transition probability of student loyalty from 0.35 to 0.47 after the first transition period and to 0.51 after the second transition period. The study provides empirical evidence that technological development significantly influences student loyalty and reduces switching behaviour. It concludes that sustained investment in technological infrastructure and digital learning support services can enhance student retention, strengthen institutional stability, and improve the competitive position of private universities. The originality of this study lies in the application of Markov Chain analysis to model student switching behaviour in Nigerian private universities, thereby providing a dynamic framework for predicting student loyalty over time.

Keywords: *Technological Change, Student Loyalty, Markov Chain, Private University, Switching Behaviour.*

Introduction

The increasing demand for higher education has outpaced institutional quality in many developing economies, leading to growing concerns regarding student loyalty and retention (Ogunnaike, Agada, Ighomereho, & Borishade, 2022). Consequently, private universities, particularly in Nigeria, are increasingly competing for student loyalty through substantial investments in technological development in order to distinguish themselves within a highly

competitive higher education sector (Usendiah et al., 2022). Nevertheless, students continue to switch from one university to another for reasons that often extend beyond institutional control, including limited programme opportunities, financial constraints, institutional reputation, and differences in the quality of learning experiences (Ajayi, 2020; Bekiros & Georgoutsos, 2005).

Previous studies have highlighted the significance of technological infrastructure in shaping students' learning experiences, satisfaction, and institutional loyalty. As universities continue to integrate advanced technologies into teaching, learning, and administrative processes, students' expectations have also evolved, influencing their decisions to remain in or transfer from an institution (Anderson et al., 2019; Puaca, 2022). These technological developments range from improved Learning Management Systems (LMS), virtual classrooms, digital libraries, and online student support services to sophisticated laboratory facilities, all of which are intended to improve learning outcomes and student satisfaction. However, the relationship between technological investment and student loyalty remains complex and is not yet fully understood, particularly within private universities operating in developing economies (De la Torre et al., 2020).

One of the emerging approaches to understanding student loyalty and switching behaviour is the application of Markov Chain models. Markov Chain analysis provides an effective quantitative technique for modelling probabilistic transitions between different behavioural states over time (Tedeschi et al., 2023). Unlike conventional statistical techniques that primarily examine relationships among variables at a particular point in time, the Markov Chain model captures the probability that students may remain loyal to their current institutions or switch to another institution following technological changes (Norris, 1997; Walters, 2000). Consequently, the model provides a dynamic framework for analysing behavioural transitions and predicting future patterns of student loyalty based on current conditions (Kerr & Li, 2021).

Although considerable attention has been devoted to technology adoption, student satisfaction, and educational quality, relatively few studies have examined how technological changes influence student switching behaviour using stochastic modelling techniques, particularly within Nigerian private universities. Existing studies have largely concentrated on the direct effects of technological infrastructure on student experiences without adequately modelling the transition probabilities associated with students' loyalty decisions over time (Wilson & Sim, 2021; Obanya et al., 2021). This methodological gap limits the understanding of how technological improvements influence students' decisions to remain in their institutions for postgraduate studies or to seek alternative institutions.

Against this background, this study applies Markov Chain analysis to model the influence of technological changes on student switching behaviour and loyalty among selected private universities in Southwest Nigeria. Specifically, the study examines how improvements in internet facilities, online library support services, laboratory facilities, and overall technological development influence students' postgraduate enrolment intentions and institutional loyalty. The findings are expected to provide quantitative evidence that will assist university administrators and policymakers in developing technology-driven strategies for improving student retention, strengthening institutional competitiveness, and promoting sustainable institutional development within Nigeria's higher education sector.

2. Review of Literature

2.1 Theoretical Framework

This study is anchored on Student Integration Theory developed by Tinto (2017), which explains students' persistence, loyalty, and retention in higher education institutions. The theory posits that students' decisions to remain in or withdraw from an institution are largely influenced by the extent to which they become academically and socially integrated into the university environment. Academic integration reflects students' satisfaction with teaching quality, learning resources, institutional support, and overall educational experiences, while social integration concerns students' sense of belonging and interaction within the university community (Tinto, 2017). The theory argues that students who experience higher levels of academic and social integration are more likely to remain loyal to their institutions and continue their educational programmes.

Within the context of this study, technological changes constitute an important aspect of the institutional environment capable of influencing students' academic experiences and loyalty. Previous studies have shown that improvements in technological infrastructure, such as Learning Management Systems (LMS), virtual classrooms, digital libraries, and internet facilities, significantly enhance students' learning experiences and institutional satisfaction (Anderson, Johnson, & Smith, 2019; De la Torre, Suárez, & Hernández, 2020). Similarly, technological innovations have been found to improve students' engagement, learning flexibility, and overall educational experience, thereby strengthening their commitment to their institutions (Adams, 2020; Bates, 2019). Conversely, inadequate technological facilities may reduce students' satisfaction and increase their intentions to transfer to alternative institutions offering better learning environments (Ajayi, 2020; Puaca, 2022).

Although Student Integration Theory provides a behavioural explanation for student loyalty and retention, it does not explain the probability of students transitioning between loyalties and switching decisions over time. Consequently, this study complements the theory with Markov Chain analysis, which provides a quantitative framework for modelling the probability of students remaining loyal to their current universities or switching to other institutions following technological changes (Norris, 1997; Walters, 2000). The Markov Chain model enables the estimation of transition probabilities based on students' responses to different technological conditions and predicts future behavioural patterns from existing states (Kerr & Li, 2021). This makes the model particularly appropriate for analysing student switching behaviour in private universities where technological development increasingly influences students' postgraduate enrolment decisions.

Accordingly, Student Integration Theory provides the behavioural foundation for explaining how technological changes influence student loyalty, while Markov Chain analysis provides the quantitative mechanism for modelling the transition probabilities associated with students' decisions to remain in their universities or switch to alternative institutions. The integration of both approaches therefore provides a comprehensive framework for understanding and predicting student switching behaviour in selected private universities in Southwest Nigeria.

2.2 Conceptual Framework

The conceptual framework for this study is derived from Student Integration Theory (Tinto, 2017) and supported by previous studies on technological change and student loyalty (Anderson et al., 2019; De la Torre et al., 2020; Wilson & Sim, 2021; Obanya, Oyekanmi, & Adesina, 2021). The framework assumes that improvements in technological infrastructure-including internet facilities, online library support services, functional laboratory equipment, and other technological innovations, enhance students' academic experiences and institutional satisfaction.

Improved satisfaction strengthens student loyalty, which in turn reduces switching behaviour and increases the likelihood of students remaining in the same institution for postgraduate studies. The transition between these behavioural states is modelled using Markov Chain analysis.

2.3 Technological Changes

Technological modernization has been at the centre of transforming various sectors, particularly higher education, by improving access to information and promoting innovative teaching and learning processes. Traditional methods of teaching and learning have been significantly transformed through the adoption of digital technologies, leading to the widespread use of e-learning platforms, virtual classrooms, digital libraries, online assessments, and other technology-enabled learning systems (Oni, Adewoye, & Eweoya, 2016). These technological innovations not only provide greater learning flexibility but also facilitate personalized learning experiences that accommodate the diverse academic needs of students (Adams, 2020). Furthermore, the rapid development and implementation of educational technologies require continuous adaptation by both students and academic staff, making technological competence an essential requirement for effective teaching and learning in contemporary higher education (Johnson, 2019). Consequently, higher education institutions are under increasing pressure to continuously upgrade their technological infrastructure in order to meet the evolving expectations of students and remain competitive within the higher education sector (Bates, 2019).

Technological improvements have also become an important determinant of student satisfaction, loyalty, and retention in higher education. The integration of Learning Management Systems (LMS), virtual learning environments, mobile learning applications, online registration systems, and digital library services has enhanced students' ability to access academic resources conveniently and participate more actively in the learning process (Smith & Jones, 2021). These developments have contributed to improved student engagement and institutional loyalty. Nevertheless, the rapid pace of technological advancement often exceeds the capacity of some institutions to effectively implement and manage emerging technologies, thereby creating disparities in technology adoption and utilization across universities (Williams, 2018). Such disparities may influence students' perceptions of institutional quality and subsequently affect their loyalty and retention decisions.

Recent studies continue to demonstrate that technologically responsive universities are better positioned to attract and retain students. Institutions that provide reliable internet connectivity, efficient online learning platforms, digital support services, and modern learning facilities generally report higher levels of student satisfaction and commitment than institutions with inadequate technological infrastructure (Ogunnaike, Agada, Ighomereho, & Borishade, 2022; Usendiah et al., 2022). Similarly, studies have shown that students who readily adapt to technological innovations are more likely to remain committed to their institutions and participate actively in academic activities (Garcia & de la Vega, 2020). These findings suggest that technological development should not merely focus on acquiring modern facilities but should also include continuous technical support, staff development, and student training to ensure the effective utilization of available technologies. Therefore, higher education institutions must continuously align technological investments with students' academic expectations and

institutional objectives in order to strengthen student loyalty and reduce the likelihood of switching behaviour.

2.4 Student Switching Behaviour

Switching behaviour among higher education students is a phenomenon where students switch institutions or drop studies altogether for a number of reasons. Switching is normally triggered by the perceived quality of education, satisfaction with academic services, and circumstances outside the learning environment, like financial limitations or a change in one's life (Thomas, 2021). Research indicates that if students are dissatisfied with the quality of learning or the overall academic setting, they are more likely to switch to a different college that meets their standards (Nora & Crisp, 2018). Further, the availability of superior opportunities elsewhere, such as access to superior facilities or more specialized courses, can also make students switch colleges (Martínez et al., 2020). Understanding these factors is critical to schools seeking to retain their students and stem dropout rates.

Switching behaviour is also very much subject to the social and cultural environment of the institution. Studies have proven that weak social integration and support in the institution may lead to students becoming isolated and alienated, and consequently, this may increase the likelihood of students switching schools (Tinto, 2017). Additionally, student loyalty is set by the cultural congruence between the student and the institution (Todea, Davidescu, Pop, & Stamule 2022). If students perceive a dissonance between their values and those of the institution, they will be predisposed to shift to alternatives that have a closer alignment to their own values and expectations (Braxton & McClendon, 2019). Policies instituted in the institution that promote a supportive and inclusive culture have the ability to minimize switching behaviour by getting to the source of student discontent and building more belonging (Kim & Lundberg, 2016). By the identification and minimization of those factors driving student switching behavior, schools are able to improve student retention and general academic attainment.

3. Methods

3.1 Research Design

The study employs a comprehensive multi-method approach, integrating both quantitative statistical methods and Markov Chain Analysis.

3.2 Population and Sample Size

The study focused on a population of 4,436 final-year students from the most patronized private universities in Southwest Nigeria. A sample size of 464 students was determined using a 95% confidence level and a 5% margin of error, as recommended by Taherdoost (2016), to represent the entire population. This sample size permits for simplifying findings while managing the challenges of studying a large population. The Markov Chain Analysis was used to model the transitions amid various technological change situations and student loyalty, providing an understanding of how these changes influence loyalty over time.

3.3 Markov Model Assumptions

An analysis of the Markov process assumes that any system addressed in the first instance must be in its initial state before transitioning to another state. This assumption is based on the concept of "Transition Probability."

The transition probabilities explain the chances of a particular case moving from one state to another during a certain period. For example, the probability of the transition phenomenon of the case (i) in the current period (n) to another state (j) in the later period (n+1). This is written as follows:

$$P\ X_{n+1} = j/X_{n\ =\ i} = Pij\ \forall i, j$$

Where: X_n is the value of the phenomenon (state) in the current period (n), X_{n+1} is the value of the Phenomenon (state) in the subsequent period (n+1).

Pij is the probability of transmission from the phenomenon of state (i) to the state (j).

Thus, before formulating a Markov chain model, there is a finite number of possible states. In this study, the finite state space refers to the number of universities offering postgraduate admission to prospective students [Covenant University, Babcock University, and Redeemer University]. The state space vector (V) can be represented in the model as:

V= [CU, BU, RU] (1)

This can also be represented by initializing the state vector (1) as follows:

V= *[1, 0, 0]* 2

Also, another assumption for analyzing the Markov chain process is that the state space is both collectively exhaustive and mutually exclusive. This implies that the transition probabilities depend only on the current state of the system; that is, if the current state is known, the conditional probability of the next state is independent of the states prior to the present state. In the current study, a prospective student cannot gain admission to more than one university at a time. In other words, a student's choice of one university, say CU precludes the choice of another university, say RU. Thus, the mutual exclusiveness assumption prevails in students' loyalty behaviour from one transition period (X_n) to the subsequent one (X_{n+1}). Similarly, the collective assumption in the case at hand implies that the universities under investigation of student loyalty transition are clearly defined.

Definition of Notations

Let S*it* denote the loyalty (state) i.

Where *s* = state space occupied by an element

Where *i* = CU, BU, RU, (the University that a student is currently enrolled in at a particular time); letter CU represents Covenant University; letter BU and RU represent Babcock and Redemer University respectively.

t= time in which the transition operation takes place for each element

P = represents the transition probability matrix

V*it* = the vector proportion of student enrolments controlled by a university *i* in period *t*; V*i0* = the initial share of student's loyalty received by a university *i* in the period *0*.

Given the above definition, the proportion of student enrolment loyalty controlled by the universities at initial time *O* initially is V = [VCU_0, VBU_0, VRU_0].

4. Results and discussion

To determine the probability of students returning to their respective universities for Master's (M.Sc.) and Doctor of Philosophy (Ph.D.) programmes as a result of technological improvements, the data were analysed using Markov Chain transition probability matrices. The transition probabilities represent the likelihood of students remaining loyal to their current institutions or switching to another institution following improvements in selected technological factors.

Table 4.1. Better Access to Internet Facilities

Institution	CU	BU	RU	Total
CU	125	31	2	158
BU	46	150	11	207
RU	43	20	27	90
Total	214	201	40	455

Source: Authors' computation from field survey (2025)

Matrix Probability of Better Access to Internet Facilities

$$\begin{array}{c} \\ \text{CU} \\ \text{BU} \\ \text{RU} \end{array} \begin{array}{c} \begin{array}{ccc} \text{CU} & \text{BU} & \text{RU} \end{array} \\ \begin{pmatrix} \mathbf{0.79} & \mathbf{0.20} & \mathbf{0.01} \\ \mathbf{0.22} & \mathbf{0.73} & \mathbf{0.05} \\ \mathbf{0.48} & \mathbf{0.22} & \mathbf{0.30} \end{pmatrix} \end{array} \begin{pmatrix} \mathbf{0.35} & \mathbf{0.45} & \mathbf{0.20} \end{pmatrix}$$

= (0.47, 0.44, 0.09)

The probability significantly increases from 35% to 47%. This indicates that with better access to internet facilities, a significant portion of users quickly become competent in utilizing these resources effectively. The probability decreases slightly from 45% to 44%. This suggests that many basic users are transitioning towards becoming competent, but there is still a substantial number in this category. While the probability decreases from 20% to 19%.

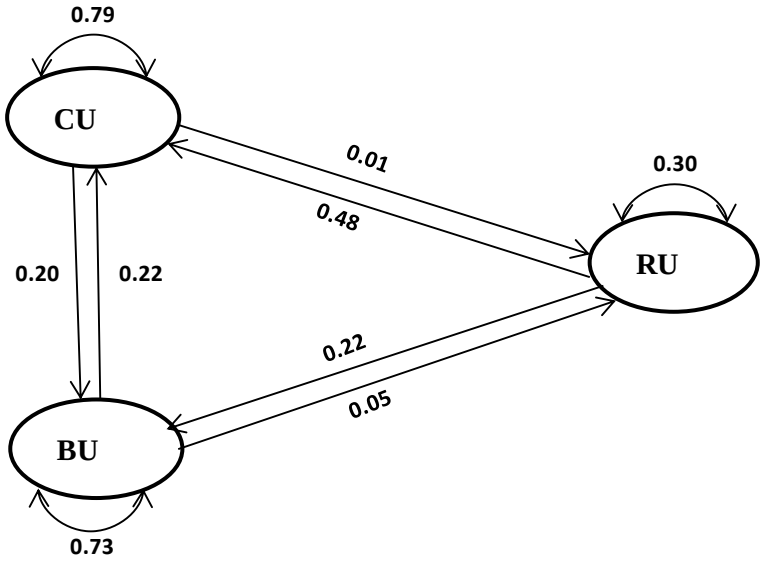
Two periods: (0.47, 0.44, 0.09)

$$\begin{array}{c} \\ \text{CU} \\ \text{BU} \\ \\ \end{array} \begin{array}{c} \begin{array}{ccc} \text{CU} & \text{BU} & \text{RU} \end{array} \\ \begin{pmatrix} \mathbf{0.79} & \mathbf{0.20} & \mathbf{0.01} \\ \mathbf{0.22} & \mathbf{0.73} & \mathbf{0.05} \\ \mathbf{0.48} & \mathbf{0.22} & \mathbf{0.30} \end{pmatrix} \end{array}$$

= (0.51, 0.44, 0.05) RU

The probability further increases to 51% for CU, indicating a continued trend towards users becoming proficient with the improved internet facilities. This reflects ongoing successful adaptation and utilization of the resources while the probability is maintained at 44% for BU. This suggests that while the basic user group is still significant, more users are moving towards competence, albeit at a slower rate compared to the first period. The probability further decreases to 5%, showing a steady decline in the number of users needing significant support. This indicates the sustained effectiveness of the support programs in helping users adapt.

Figure 4.1: Markov Chain Transitions (Better Access to Internet Facilities)



Source: Authors' computation from field survey (2025)

Table 4.2. Better Access to Library Online Support Services

Institution	CU	BU	RU	Total
CU	134	19	5	158
BU	48	146	13	207
RU	16	43	31	90
Total	198	208	49	455

Source: Authors' computation from field survey (2025)

Matrix Probability of Better Access to Library Online Support Services

$$\begin{array}{c} \\ CU \\ BU \\ RU \end{array}\begin{array}{c} \begin{array}{ccc} CU & BU & RU \end{array} \\ \begin{pmatrix} \mathbf{0.85} & \mathbf{0.12} & \mathbf{0.03} \\ \mathbf{0.23} & \mathbf{0.71} & \mathbf{0.06} \\ \mathbf{0.18} & \mathbf{0.48} & \mathbf{0.34} \end{pmatrix} \end{array} \quad \begin{pmatrix} \mathbf{0.35} & \mathbf{0.45} & \mathbf{0.20} \end{pmatrix}$$

= (0.437, 0.4575, 0.1055)

The probability increases from 35% to 43.7% for CU. This indicates that improved access to library online support services enables a significant portion of users to become more competent in utilizing these resources. The probability increases from 45% to 45.75% for BU, this suggests that some basic users are moving towards competence, but many remain in this category, highlighting the need for ongoing support and training. However, the probability for RU decreases from 20% to 10.55% showing a reduction in the number of users who struggle with adapting to the new services, indicating that initial interventions are somewhat effective but could be improved

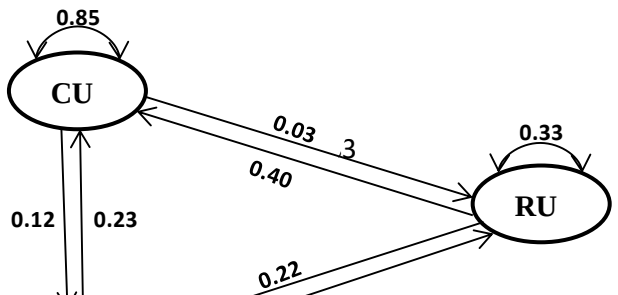
Two periods: (0.437, 0.4575, 0.1055)

$$\begin{array}{c} \\ CU \\ BU \\ RU \end{array}\begin{array}{c} \begin{array}{ccc} CU & BU & RU \end{array} \\ \begin{pmatrix} \mathbf{0.84} & \mathbf{0.12} & \mathbf{0.03} \\ \mathbf{0.23} & \mathbf{0.70} & \mathbf{0.06} \\ \mathbf{0.18} & \mathbf{0.27} & \mathbf{0.34} \end{pmatrix} \end{array}$$

= (0.49, 0.43, 0.08)

The probability further increases to 49% for CU, showing a continued trend of users becoming proficient with the enhanced online library services. This reflects the success of the support programs in fostering competence over time. Furthermore, the probability decreases to 43% for BU, indicating that a significant portion of users are transitioning from basic to competent users. This suggests that with sustained effort, more users are expected to become proficient. While another probability further decreases to 8%, showing a steady decline in the number of users needing substantial support.

Figure 4.2: Markov Chain Transitions (Better Access to Internet Facilities)



Source: Authors' computation from field survey (2025)

Table 4.3 Functional and Sophisticated Laboratory Equipment for Advanced Research

Institution	CU	BU	RU	Total
CU	128	27	3	158
BU	38	151	18	207
RU	28	27	35	90
Total	194	205	56	455

Source: Authors' computation from field survey (2025)

Matrix Probability of Functional and Sophisticated Laboratory Equipment for Advanced Research

$$\begin{array}{c} \\ CU \\ BU \\ RU \end{array} \begin{array}{c} \begin{array}{ccc} CU & BU & RU \end{array} \\ \begin{pmatrix} \mathbf{0.81} & \mathbf{0.17} & \mathbf{0.02} \\ \mathbf{0.18} & \mathbf{0.73} & \mathbf{0.09} \\ \mathbf{0.31} & \mathbf{0.30} & \mathbf{0.39} \end{pmatrix} \end{array} \begin{pmatrix} \mathbf{0.35} & \mathbf{0.45} & \mathbf{0.20} \end{pmatrix}$$

= (0.4265, 0.448, 0.1255)

The probability increases from 35% to 42.65%. This indicates that the introduction of advanced lab equipment has a positive impact on user competence, enabling more users to efficiently utilize these resources. The probability slightly decreases from 45% to 44.8%. While many users remain in the basic category, there is a trend towards increased competence, showing that some users are beginning to adapt to the new equipment. The probability decreases from 20% to 12.55%. This decrease suggests that fewer users are struggling with the transition, reflecting the effectiveness of functional laboratories.

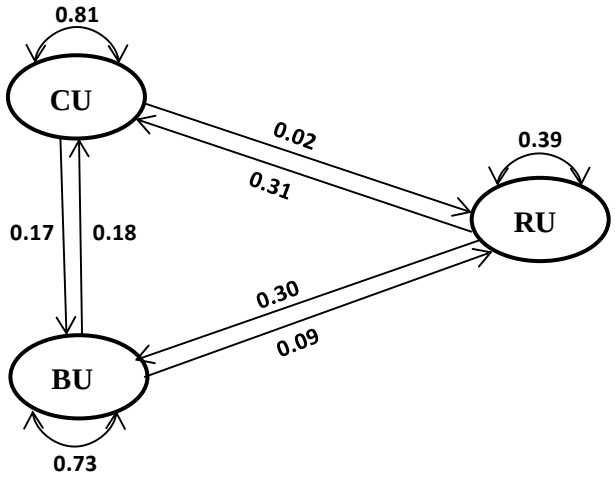
Two periods: (0.4265, 0.448, 0.1255)

	CU	BU	RU
CU	**0.81**	**0.17**	**0.02**
BU	**0.18**	**0.73**	**0.09**
RU	**0.31**	**0.30**	**0.39**

= (0.46, 0.44, 0.10)

The probability further increases to 46% for CU, indicating continued growth in user competence over time. As users become more familiar with the advanced equipment, their ability to effectively use these resources improves. The probability decreases to 44% for BU, suggesting a further reduction in the number of basic users as more of them transition to the competent category. The probability continues to decrease to 10% for RU, showing sustained improvement in user adaptability and a decrease in the number of users needing significant support.

Figure 4.3: Markov Chain Transitions (Functional and Sophisticated Laboratory Equipment for Advanced Research)



Source: Authors' computation from field survey (2025)

Table 4.4 Overall changes in the University's Technological-related issues

Institution	CU	BU	RU	Total
CU	127	23	8	158
BU	33	145	29	207
RU	20	35	35	90

Total	180	203	72	455

Matrix Probability of Overall changes in the University's Technological-related issues

$$\begin{array}{c} \\ CU \\ BU \\ RU \end{array} \begin{array}{c} \begin{array}{ccc} CU & BU & RU \end{array} \\ \begin{pmatrix} \mathbf{0.80} & \mathbf{0.15} & \mathbf{0.05} \\ \mathbf{0.16} & \mathbf{0.70} & \mathbf{0.14} \\ \mathbf{0.22} & \mathbf{0.39} & \mathbf{0.39} \end{pmatrix} \end{array} \quad \begin{pmatrix} \mathbf{0.35} & \mathbf{0.45} & \mathbf{0.20} \end{pmatrix}$$

= (0.40 0.44 0.16)

The probability of being in the CU state increases from 35% to 40%. The probability of being in the BU state decreases from 45% to 44%. The probability of being in the RU state increases from 20% to 16%. This suggests that the system is transitioning towards a higher concentration in the CU state, indicating a focus on addressing the overall technological-related issues at the university.

Two periods:

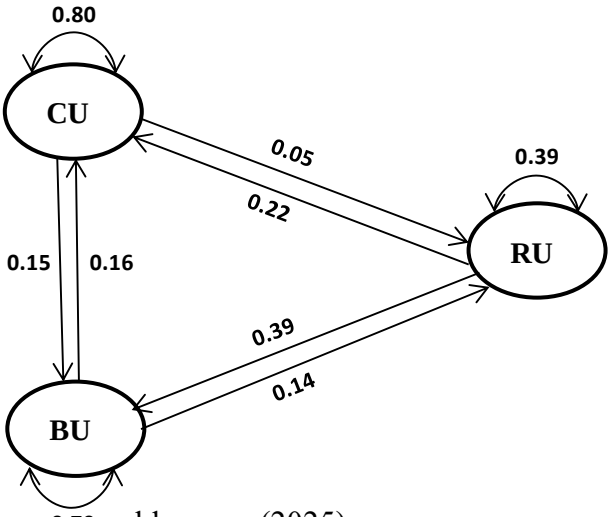
$$\begin{array}{c} \\ CU \\ BU \\ RU \end{array} \begin{array}{c} \begin{array}{ccc} CU & BU & RU \end{array} \\ \begin{pmatrix} \mathbf{0.80} & \mathbf{0.15} & \mathbf{0.05} \\ \mathbf{0.16} & \mathbf{0.70} & \mathbf{0.14} \\ \mathbf{0.22} & \mathbf{0.39} & \mathbf{0.39} \end{pmatrix} \end{array}$$

$$= \begin{pmatrix} \mathbf{0.68} & \mathbf{0.24} & \mathbf{0.08} \\ \mathbf{0.27} & \mathbf{0.57} & \mathbf{0.16} \\ \mathbf{0.32} & \mathbf{0.46} & \mathbf{0.22} \end{pmatrix} \quad \begin{pmatrix} \mathbf{0.35} & \mathbf{0.45} & \mathbf{0.20} \end{pmatrix}$$

= (0.42, 0.43, 0.15)

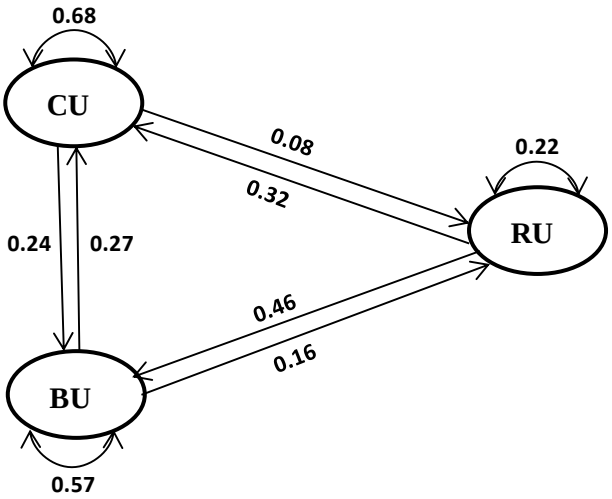
The probability of being in the CU state further increases to 42%. The probability of being in the BU state slightly decreases to 43%. The probability of being in the RU state continues to decrease to 15%. This trend suggests that the system is stabilizing towards a higher concentration in the CU state, reinforcing the focus on changes in the University's technological-related issues.

Markov Chain Transition (Overall changes in the University's Technological-related issues)



Source: Authors' computation eld survey (2025)

Figure 4.4; *Markov Chain Transition for MSc Students.*



Source: Authors' computation from field survey (2025)

Figure 4.5 *Markov Chain Transition for Students returning for PhD studies*

TABLE 4.5 PROBABILITY DISTRIBUTION OF RESPONDENTS

S/N	ITEMS	M.Sc			Ph.D		
		CU	BU	RU	CU	BU	RU
1	Better Access to Internet Facilities	0.46	0.44	0.10	0.50	0.44	0.06

2	Better Access to Library Online Support Services	0.437	0.4575	0.1055	0.49	0.43	0.08
3	Functional and Sophisticated Laboratory Equipment for Advanced Research	0.4265	0.448	0.1255	0.46	0.44	0.10
4	Overall changes in the University's Technological-related issues	0.40	0.44	0.16	0.4256,	0.4304	0.144

Source: Authors' computation from field survey (2025)

TABLE 4.6 PROBABILITY DISTRIBUTION OF STUDENTS THAT MAY RETURN TO THEIR UNIVERSITY FOR PG PROGRAMME

From the findings, we can deduce in the Table below the probability of Students coming back for MSc and Ph.D programmes in their Universities due to the technological changes made in their Universities.

S/N	ITEMS	M.Sc			Ph.D		
		CU	BU	RU	CU	BU	RU
1	Returning Students	0.80	0.70	0.39	0.68	0.57	0.22

Source: Authors' computation from field survey (2025)

4.1 Discussion of Findings

The findings of this study demonstrate that technological changes significantly influence student loyalty and switching behaviour among selected private universities in Southwest Nigeria. The Markov Chain transition probabilities consistently show that improvements in internet facilities, online library support services, laboratory equipment, and overall technological infrastructure increase the likelihood of students remaining loyal to their institutions for postgraduate studies. These findings suggest that technological investments contribute not only to improved learning experiences but also to students' long-term commitment to their universities.

The findings are consistent with the work of Adams (2020), who reported that digital learning platforms enhance student engagement and institutional commitment by improving learning flexibility and accessibility. Similarly, Bates (2019) argued that universities that continuously invest in modern technological infrastructure are better positioned to improve student satisfaction and institutional competitiveness. The present study extends these findings by demonstrating, through Markov Chain analysis, how technological improvements influence the probability of students remaining loyal to their institutions over successive transition periods rather than merely establishing statistical associations.

The results also support the findings of Anderson, Johnson, and Smith (2019) and Puaca (2022), who observed that effective integration of educational technologies enhances students' academic experiences and encourages continued enrolment. Likewise, De la Torre, Suárez, and Hernández (2020) reported that technological innovation has become an important determinant of students' institutional choice and retention. The present study confirms these observations within the context of Nigerian private universities by showing that improved technological infrastructure increases the probability of students remaining in their current institutions for postgraduate education.

Furthermore, the findings agree with Tinto's (2017) Student Integration Theory, which explains that students are more likely to remain in an institution when they experience a supportive academic environment. Improvements in internet access, online learning resources, digital support services, and laboratory facilities strengthen students' academic integration by providing better learning opportunities and reducing barriers to academic success. Consequently, these improvements enhance institutional loyalty and reduce students' intentions to transfer to alternative universities.

The application of Markov Chain analysis provides additional insight beyond previous studies by modelling the transition probabilities associated with student loyalty and switching behaviour over time. While earlier studies primarily examined the relationship between technological infrastructure and student satisfaction using conventional statistical approaches (Johnson, 2019; Smith & Jones, 2021), the present study demonstrates the dynamic nature of students' loyalty decisions by estimating the probability of remaining in or leaving an institution under different technological conditions. This illustrates the suitability of Markov Chain analysis for modelling behavioural transitions in higher education.

Although the overall findings indicate positive effects of technological improvements on student loyalty, differences in transition probabilities across the three universities suggest that technological infrastructure alone may not completely explain students' postgraduate enrolment decisions. Institutional reputation, academic quality, financial considerations, availability of postgraduate programmes, and students' personal career aspirations may also influence loyalty and switching behaviour (Thomas, 2021; Nora & Crisp, 2018; Martínez et al., 2020). These factors may explain why some technological improvements produced stronger transition probabilities in one institution

Conclusion

This study examined the influence of technological changes on student loyalty and switching behaviour among selected private universities in Southwest Nigeria using Markov Chain analysis. The findings demonstrate that improvements in technological infrastructure, including better internet facilities, online library support services, functional laboratory equipment, and overall technological development, increase the probability of students remaining loyal to their institutions and returning for postgraduate studies. The transition probability analysis further shows that technological improvements can positively influence students' long-term enrolment decisions by reducing the likelihood of switching to competing institutions.

A major contribution of this study is the application of the Markov Chain model to explain student loyalty as a dynamic transition process rather than a static behavioural outcome. Unlike conventional statistical approaches that primarily examine relationships among variables, the Markov Chain approach provides a probabilistic framework for predicting students' future

loyalty behaviour under changing technological conditions. This offers university managers and policymakers a practical decision-support tool for planning technology investments that strengthen student retention and institutional competitiveness.

Despite these contributions, the study has certain limitations. The analysis was based on data collected from final-year students in three selected private universities in Southwest Nigeria. Consequently, the findings may not be fully generalisable to public universities or private universities in other regions of the country. In addition, the study focused primarily on technological factors influencing student loyalty, whereas other determinants, such as institutional reputation, tuition costs, academic quality, employability prospects, and socio-economic factors, were not incorporated into the Markov Chain model.

Future research should extend this study by including a larger sample of universities across different geopolitical zones in Nigeria and by integrating additional institutional and behavioural variables into the transition model. Longitudinal studies that monitor students over multiple academic periods would also provide a better understanding of changes in loyalty and switching behaviour over time. Furthermore, future studies may combine Markov Chain analysis with other quantitative techniques, such as Structural Equation Modelling (SEM), to examine both the causal relationships among technological variables and the long-term transition probabilities associated with student loyalty.

Recommendations

Based on the findings of this study, the following recommendations are proposed:

1. Private university management should prioritise continuous investment in technological infrastructure, including reliable internet connectivity, digital libraries, virtual learning platforms, and modern laboratory facilities. Regular technological upgrades will improve students' learning experiences, strengthen institutional loyalty, and increase the likelihood of students returning for postgraduate studies.

2. Universities should establish comprehensive digital support services by providing continuous training and technical assistance for students, academic staff, and administrative personnel. Such support will improve users' ability to utilise technological facilities effectively and minimise dissatisfaction arising from technological challenges.

3. Institutional digital transformation strategies should be integrated into university strategic planning. Technology investments should be guided by students' academic needs and regularly evaluated to ensure that technological innovations contribute to improved teaching, learning, research productivity, and student retention.

4. University administrators should implement periodic monitoring and evaluation of student loyalty and retention patterns. Applying analytical approaches such as Markov Chain modelling can assist management in predicting future student retention trends and identifying areas requiring timely intervention before significant student attrition occurs.

5. Regulatory agencies, including the National Universities Commission (NUC), should encourage and support technology-driven institutional development by providing policy

guidelines, research grants, and digital infrastructure intervention programmes that enhance the competitiveness of private universities in Nigeria.

6. University management should strengthen complementary non-technological factors that influence student loyalty, including academic quality, effective student support services, institutional reputation, career development opportunities, and a supportive learning environment. Technological improvements are most effective when combined with strong institutional support systems.
7. Future institutional planning should adopt evidence-based decision-making by integrating quantitative predictive models, including Markov Chain analysis, into enrolment planning, postgraduate admission forecasting, and student retention strategies. This will enable universities to make proactive decisions that improve institutional sustainability and long-term competitiveness.

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