

Original Article

Profiling At-Risk Student Characteristics Associated with Mandatory Programmatic Divergence in Licensure-Based Programs at a Private University

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Abstract. Student attrition remains a major concern in higher education, particularly in licensure-based programs with rigorous academic standards and retention policies. This study aimed to statistically profile at-risk students associated with mandatory programmatic divergence and provide baseline evidence for the development of institutional retention initiatives and an Early Warning System. The study was conducted at the study institution using a descriptive cross-sectional quantitative research design that combined secondary institutional records and primary survey responses. A total of 220 undergraduate students identified as at risk of mandatory programmatic divergence were selected through proportionate stratified random sampling. The study examined socio-demographic attributes, academic background, institutional retention indicators, and attrition-related factors categorized into academic, financial, and personal-social dimensions. Data were analyzed using frequency counts, percentages, means, standard deviations, the Mann-Whitney U test, and the Kruskal-Wallis H test. The findings showed that most at-risk students were female, belonged to the middle-income group, and were enrolled in the second and third year levels. Academic factors ($M = 3.42$, $SD = 0.88$) and personal-social factors ($M = 3.46$, $SD = 0.65$) were rated as Frequently Occurred, whereas financial factors ($M = 3.08$, $SD = 1.18$) were rated as Sometimes Occurred. Significant differences in academic background were observed across sex, income level, previous course, and present course, while institutional retention indicators differed significantly according to year level. The findings provide a statistical profile of at-risk students in licensure-based programs and offer baseline evidence that may inform institutional retention strategies, student support initiatives, and the future development of an Early Warning System.

Keywords: *At-risk students; Early warning system; Licensure-based programs; Mandatory programmatic divergence; Student attrition.*

Student attrition remains a major concern in higher education because it affects student persistence, graduation outcomes, institutional sustainability, and educational quality. Attrition refers to students' withdrawal, transfer, discontinuation, or failure to complete their academic programs. In licensure-based programs, this concern becomes more critical because students must meet rigorous academic standards, retention policies, progression requirements, and professional competencies that affect their ability to continue in their chosen programs.

In this context, mandatory programmatic divergence refers to an institutional retention mechanism that requires students to transfer to another academic program after failing to meet prescribed academic retention standards, progression requirements, or competency benchmarks established for licensure-based programs. Unlike voluntary program shifting initiated by students, mandatory programmatic divergence is implemented by the institution to ensure that students who cannot meet program-specific academic requirements are redirected to more appropriate degree programs while maintaining opportunities for academic completion. Such policies are common among licensure-based programs in the Philippines, particularly in disciplines such as Accountancy, Nursing, Pharmacy, Medical Laboratory Science, and Engineering, where institutional retention policies and professional accreditation requirements govern progression.

Recent studies on student retention have increasingly utilized predictive analytics, learning analytics, and Early Warning Systems to identify students at risk of attrition. Foster and Siddle (2020), Bañeres et al. (2020), Jivet et al. (2020), Jovanović et al. (2021), Mduma et al. (2023), Bañeres et al. (2023), Goren et al. (2024), Vaarma and Li (2024), and Dai et al. (2025) demonstrated the usefulness of academic records, demographic characteristics, learning behaviors, and institutional data in identifying students requiring timely intervention. However, these studies primarily emphasized predictive accuracy and machine-learning performance rather than developing multidimensional statistical profiles of students affected by institution-specific retention policies.

In the Philippine higher education context, universities offering licensure-based programs commonly implement retention policies that require students to maintain minimum grades, pass qualifying examinations, or meet progression standards before advancing to higher-level professional courses. These institutional mechanisms aim to ensure academic quality and licensure readiness; however, they may also increase students' vulnerability to mandatory programmatic divergence when they do not meet academic standards. Despite the widespread implementation of such policies, empirical evidence remains limited on the characteristics of students affected by mandatory programmatic divergence and the factors associated with their academic vulnerability.

This study addresses this gap by examining student attrition within the context of mandatory programmatic divergence in licensure-based programs. Rather than focusing solely on dropout prediction, the study develops a multidimensional statistical profile of at-risk students by examining socio-demographic characteristics, academic background, student retention indicators, and academic, financial, and personal-social factors associated with mandatory programmatic divergence.

The study is anchored on four complementary theoretical perspectives. Tinto's Student Integration Theory (1993) explains student persistence through academic and social integration and provides the basis for examining academic background, student retention indicators, and personal-social factors. Bean and Metzner's Student Attrition Model (1985) emphasizes the influence of environmental conditions and nonacademic variables, supporting the inclusion of socio-demographic characteristics and financial factors. Astin's Student Involvement Theory (1999) highlights the importance of academic engagement and institutional participation, providing the framework for examining academic experiences and institutional support mechanisms. Finally, Bandura's Self-Efficacy Theory (1977) explains how students' confidence, coping ability, and perceived academic competence relate to personal-social factors and persistence in academically demanding programs.

Specifically, this study aimed to (a) describe the socio-demographic characteristics of at-risk students enrolled in selected licensure-based programs; (b) examine the academic background, student retention indicators, and attrition-related factors of at-risk students; (c) determine significant differences in academic background and student retention indicators when respondents are grouped according to selected socio-demographic characteristics; and (d) provide baseline evidence to support the development of institutional retention initiatives and an Early Warning System for students enrolled in licensure-based programs.

Methodology

Research Design

The researchers employed a descriptive-comparative, cross-sectional quantitative research design to examine the characteristics of students identified as at risk of mandatory programmatic divergence in selected licensure-based programs at the study institution. The descriptive component profiled respondents by socio-demographic

characteristics, academic background, student retention indicators, and academic, financial, and personal-social factors. The comparative component examined differences in selected variables across socio-demographic groups using nonparametric statistical procedures. Because data were collected at a single point in time, the study adopted a cross-sectional approach. This research design was appropriate because the study sought to describe and compare the characteristics of institutionally identified at-risk students without manipulating any variables or establishing causal relationships.

As a cross-sectional investigation, the study describes conditions observed during the data collection period and identifies statistical differences among respondent groups. The findings should not be interpreted as evidence of causality or as predictors of mandatory programmatic divergence because the study did not include a comparison group of non-at-risk students. Instead, the results provide a statistical profile of institutionally identified at-risk students that may serve as baseline information for institutional retention initiatives and the future development of an Early Warning System. Future longitudinal and comparative studies involving both at-risk and non-at-risk students are recommended to examine predictors of mandatory programmatic divergence over time.

Participants and Sampling Technique

The researchers conducted the study at the study institution. The target population consisted of 416 undergraduate students institutionally identified as at risk of mandatory programmatic divergence and officially enrolled during the data collection period. The minimum required sample size was computed using Slovin's formula with a 5% margin of error, yielding 204 respondents. To improve sample representativeness, ensure adequate proportional allocation across the participating licensure-based programs, and allow for potential nonresponse, the sample size was increased to 220 respondents. The researchers selected the final sample using proportionate stratified random sampling. The respondents were selected from the University's licensure-based programs, namely Accountancy, Nursing, Pharmacy, Medical Laboratory Science, and Engineering. Students were classified as at risk of mandatory programmatic divergence based on the University's retention policy, specifically those who failed to maintain the required General Weighted Average (GWA) of at least 85 and/or incurred failing grades in one or more professional courses or a total of 9 units, thereby placing them at risk of being required to shift to another academic program.

The study included undergraduate students who (1) were officially enrolled in the selected licensure-based programs during the study period; (2) were institutionally identified as at risk of mandatory programmatic divergence based on established retention criteria; and (3) voluntarily agreed to participate in the survey. The study excluded students enrolled in non-licensure programs, graduates, inactive students, and those with incomplete institutional or survey records. The researchers used proportionate stratified random sampling, with academic program and sex as the primary strata, to ensure each subgroup was represented in proportion to its share of the target population. This sampling technique minimized sampling bias and improved sample representativeness. The final sample consisted of 220 respondents, all of whom completed the survey, resulting in a 100% response rate.

Research Instrument

The researchers utilized two primary research instruments for data collection: (1) Historical Data Extraction Form for secondary institutional data and (2) Structured Survey Questionnaire for primary respondent data. Together, these instruments enabled the study to capture both objective institutional indicators and perceived experiences of attrition associated with mandatory programmatic divergence.

Historical Data Extraction Form

The researchers developed the Historical Data Extraction Form to gather secondary data from institutional academic records and student information databases. The extracted variables included socio-demographic characteristics (sex, residence classification, income category), academic background indicators (previous course, current course, year level, admission performance), institutional retention indicators (academic standing, retention status, progression records, grade performance), and mandatory programmatic divergence indicators. The researchers reviewed records with incomplete or inconsistent information against institutional sources. They excluded cases with substantial missing data and corrected minor missing entries when verified information was available. The researchers linked institutional records and survey responses using unique coded identifiers assigned to each participant. The coded identifiers enabled secure matching of survey responses with institutional academic records while preserving respondent anonymity. After matching, we reviewed the datasets for duplicate

records, inconsistencies, and discrepancies. When discrepancies were identified, official institutional records served as the primary reference source because they represented verified university documentation. The researchers excluded cases with unresolved inconsistencies from the final dataset to maintain data integrity and analytical accuracy.

Structured Survey Questionnaire

The researchers developed a structured questionnaire based on the literature on student attrition, retention, and Early Warning Systems, as well as the theoretical frameworks of Tinto (1993), Bean and Metzner (1985), Astin (1999), and Bandura (1977). The questionnaire measured factors associated with mandatory programmatic divergence among students enrolled in licensure-based programs. The questionnaire consisted of thirty-two (32) items distributed across four domains: (a) Academic Factors: seven (7) items measuring learning difficulties, academic workload, failed subjects, study habits, and classroom performance; (b) Financial Factors: seven (7) items measuring educational expenses, financial constraints, and availability of financial support; (c) Institutional Factors: twelve (12) items measuring perceptions of retention policies, academic support services, advising, and institutional requirements; and (d) Personal-Social Factors: six (6) items measuring stress, motivation, emotional well-being, peer relationships, and family support. Each item was rated using a five-point Likert scale. Each domain included multiple indicators to establish multidimensional at-risk student profiles and identify academic tipping points associated with mandatory programmatic divergence.

Validity and Reliability of the Instrument

Three experts with experience in higher education, educational research, and student services conducted content validation of the Structured Survey Questionnaire. The validation process followed the evaluation criteria proposed by Good and Scates (1972), which assess an instrument's relevance, clarity, adequacy, and appropriateness for measuring the intended constructs. The three validators assigned mean ratings of 4.46, 4.69, and 4.46, resulting in an overall mean expert validation rating of 4.54, interpreted as Excellent. Because the reported value represents the average of expert ratings rather than a conventional Content Validity Index (CVI) ranging from 0 to 1, it is more appropriately described as a mean expert validation rating.

To establish the instrument's reliability, we pilot-tested the structured questionnaire with 30 respondents not included in the final sample. We assessed internal consistency using Cronbach's alpha coefficient. The results indicated good reliability as shown in Table 1.

Table 1. Statistical Reliability of the Instrument

Domain	Cronbach's Alpha (α)	Interpretation
Academic Factors	0.83	Good Reliability
Financial Factors	0.82	Good Reliability
Institutional Factors	0.85	Good Reliability
Personal-Social Factors	0.69	Borderline Acceptable Reliability
Tipping Points	0.89	High Reliability
Overall Instrument	0.86	High Reliability

Data Gathering Procedure

Data collection was conducted from April 16, 2026, to April 23, 2026. The Office of the Registrar provided secondary data after approving the request to access institutional records. The extracted data included socio-demographic characteristics, academic background, student retention indicators, and institutional records related to mandatory programmatic divergence. The study extracted only the variables needed to address the study objectives from the institutional database. Eligible participants were identified from the University's official list of students classified as at risk of mandatory programmatic divergence based on established institutional retention criteria. We recruited participants through students' official study institution email accounts, where we sent an invitation containing the participant information sheet, informed consent form, and Google Forms survey link.

Data Analysis Procedure

Before statistical analysis, the researchers prepared the data to ensure the dataset's completeness, accuracy, and consistency. The researchers reviewed institutional records and survey responses for duplicate entries, coding errors, and missing values. Cases with substantial missing information were excluded from the analysis, whereas minor inconsistencies were verified using official institutional records whenever possible. Missing responses in the survey data were minimal (less than 5% for any variable) and were handled using pairwise deletion to

maximize the number of observations available for each analysis. Because the proportion of missing data was small, we did not perform imputation.

We examined the distributional characteristics of the study variables using normality tests. The analyses indicated that several variables deviated from normality and that the questionnaire responses were measured using ordinal Likert-scale data. Accordingly, nonparametric statistical methods were employed because they do not require the assumption of normality and are appropriate for analyzing ordinal data and comparing independent groups. Descriptive statistics summarized the respondents' socio-demographic characteristics. Frequency counts and percentages described categorical variables such as sex, residence, income level, previous course, present course, and year level. For the questionnaire domains (academic, financial, institutional, and personal-social factors), means and standard deviations summarized respondents' ratings and facilitated comparison with previous studies using similar Likert-scale instruments. Although the normality assessment indicated deviations from normality and the data were analyzed using nonparametric statistical procedures, using means and standard deviations for descriptive purposes is widely accepted in educational and social science research involving aggregated Likert-scale responses.

To address the research objectives, descriptive statistics were used to profile the respondents and summarize their academic background, student retention indicators, and attrition-related factors. Differences in academic background and student retention indicators (dependent variables) across sex, residence, income level, previous course, present course, and year level (independent grouping variables) were examined using the Mann-Whitney U test for two-group comparisons and the Kruskal-Wallis H test for comparisons involving three or more independent groups. All statistical analyses were performed using IBM SPSS Statistics. Statistical significance was evaluated at the 0.05 level ($\alpha = .05$). The assumptions for the Mann-Whitney U and Kruskal-Wallis H tests included independent observations, ordinal or continuous dependent variables, and independent grouping variables. For statistically significant Kruskal-Wallis results. No post hoc pairwise comparisons were conducted; therefore, only the overall group differences are reported.

Ethical Considerations

Prior to data collection, the researchers obtained the necessary institutional permissions and ethical approval to ensure compliance with research ethics and data privacy regulations. Ethical clearance was granted by the Research and Publication Services Research Ethics Review Committee under Protocol No. 2025-441. Before completing the questionnaire, participants received an informed consent statement explaining the study's purpose, research procedures, potential risks and benefits, the voluntary nature of participation, confidentiality of responses, and their right to decline participation or withdraw at any time without penalty or adverse academic consequences. Participants provided electronic consent before accessing the survey questionnaire. Submission of the completed questionnaire was considered evidence of informed consent. To ensure confidentiality and protect participants' privacy, we removed all personally identifiable information from the institutional dataset and replaced it with unique coded identifiers before data analysis. Institutional records and survey responses were linked only through these coded identifiers. The master file containing the coded dataset was accessible only to the researcher. All research data were used exclusively for the purposes of this study and were not disclosed to any unauthorized individual. In accordance with the approved ethics protocol, the research data will be retained for one (1) year, from April 15, 2026, to April 7, 2027. After the retention period, all electronic files, coded datasets, and related research documents will be permanently deleted and securely discarded, ensuring no identifiable participant information is retained beyond the approved retention period.

Results and Discussion

Socio-Demographic Attributes of At-Risk Students

Table 2 presents the socio-demographic attributes of respondents identified as at risk for mandatory programmatic divergence. The findings showed that female respondents comprised most of the at-risk population with 151 respondents (69%), while male respondents accounted for 69 respondents (31%). In terms of residence, 97 respondents (44%) came from Iloilo City, 88 respondents (40%) resided in rural areas, and 35 respondents (16%) came from areas outside Iloilo. Regarding family income, most respondents were in the middle-income category, with 135 respondents (61%), followed by low-income respondents with 61 students (28%) and high-income respondents with 24 students (11%).

Table 2. *Socio-Demographic Attributes of At-Risk Students*

Variable	Category	Frequency	Percentage
Sex	Male	69	31%
	Female	151	69%
Residence	Iloilo City	97	44%
	Rural Areas	88	40%
	Outside Iloilo	35	16%
Income	Low Income	61	28%
	Middle Income	135	61%
	High Income	24	11%
Year Level	First Year	23	10%
	Second Year	63	29%
	Third Year	85	39%
	Fourth Year	49	22%

Year-level distribution revealed that attrition risks were concentrated during the middle stages of academic progression, particularly among third-year students with 85 respondents (39%), followed by second-year students with 63 respondents (29%), fourth-year students with 49 respondents (22%), and first-year students with 23 respondents (10%). These findings suggest that students become increasingly vulnerable to mandatory programmatic divergence during the second and third years, where academic requirements and retention standards become more demanding. The results support Tinto's (1993) proposition that limited academic integration increases the likelihood of attrition, while Bean and Metzner (1985) highlighted those environmental conditions, such as financial circumstances, influence student persistence.

Academic Background of At-Risk Students

Table 3. *Academic Background of At-Risk Students*

Previous Program	Frequency	Percentage
BS Accountancy	125	57%
BS Nursing	22	10%
BS Pharmacy	20	9%
BS Medical Laboratory Science	18	8%
Engineering Programs	13	6%
Architecture	11	5%
Others	11	5%

Table 3 presents the academic background of respondents based on their previous programs before mandatory programmatic divergence. The findings revealed that the largest proportion of respondents previously came from the BS Accountancy program with 125 students (57%), followed by BS Nursing with 22 students (10%), BS Pharmacy with 20 students (9%), BS Medical Laboratory Science with 18 students (8%), Engineering programs with 13 students (6%), Architecture with 11 students (5%), and other programs with 11 students (5%). The concentration of respondents from BS Accountancy indicates that academically rigorous, retention-intensive programs are more susceptible to mandatory programmatic divergence. The findings suggest that students in programs with strict progression policies and high academic expectations face greater academic challenges that may increase attrition risk. These findings support Astin's (1999) Theory of Student Involvement, which explains that academic engagement influences persistence and educational outcomes. Similarly, Pascarella and Terenzini (2005) emphasized that demanding academic environments may increase stress and reduce persistence.

Institutional Retention Indicators and Attrition Factors

Table 4. *Institutional Retention Indicators and Attrition Factors*

Variable	<i>M</i>	<i>SD</i>	Interpretation
Academic Factors	3.42	0.88	Frequently Occurred
Financial Factors	3.08	1.18	Sometimes Occurred
Personal-Social Factors	3.46	0.65	Frequently Occurred
Institutional Retention Indicators	3.97	0.68	High

Table 4 presents the institutional retention indicators and factors contributing to student attrition. The findings indicated that personal-social factors obtained the highest mean score ($M = 3.46$, $SD = 0.65$), interpreted as

Frequently Occurred, followed by academic factors ($M = 3.42$, $SD = 0.88$) with the same interpretation. Financial factors recorded a lower mean of 3.08 ($SD = 1.18$) and were interpreted as Sometimes Occurred. Institutional retention indicators received the highest overall evaluation, with a mean score of 3.97 ($SD = 0.68$), interpreted as High. The results indicate that academic and personal-social concerns were associated with student vulnerability, while financial concerns showed a moderate influence. The relatively high institutional retention indicators mean further suggest that institutional standards, retention policies, and academic expectations significantly shaped student experiences and progression outcomes.

The findings indicate that academic and personal-social concerns were associated with student vulnerability, suggesting that attrition among students enrolled in licensure-based programs extends beyond academic deficiencies. Personal-social factors obtained the highest mean score ($M = 3.46$), indicating that emotional adjustment, stress management, peer relationships, and coping mechanisms substantially influenced persistence behaviors. These findings align with Bandura's Self-Efficacy Theory, which explains that perceived capability and emotional regulation influence motivation, persistence, and performance outcomes. Foster and Siddle (2020) reported similar observations and showed that learning analytics models become more effective when they examine academic indicators alongside learner support variables and institutional experiences. Likewise, Jivet et al. (2020) emphasized that self-regulated learning behaviors affect how students respond to academic feedback and intervention systems. The results, therefore, suggest that institutional retention efforts should incorporate psychosocial support alongside academic remediation.

Academic Tipping Points and Mandatory Programmatic Divergence

Table 5. *Academic Tipping Points According to Year Level*

Academic Stage	Interpretation
First Year	Emerging Risk
Second Year	Higher Concentration of At-Risk Students
Third Year	Higher Concentration of At-Risk Students
Fourth Year	Moderate Risk

Table 5 presents the academic tipping points associated with mandatory programmatic divergence according to year level. The findings identified the second and third years as strong academic tipping points, while first-year students showed emerging risk and fourth-year students showed moderate risk. This pattern aligns with the socio-demographic findings, where 63 respondents (29%) were in the second year, and 85 respondents (39%) were in the third year. The concentration of respondents in these academic stages indicates that attrition risks become more pronounced during periods characterized by major professional subjects, retention evaluations, and intensified academic requirements.

The concentration of at-risk students during the second and third years reflects a developmental transition period where students encounter major professional courses, higher retention requirements, and intensified academic workloads. These findings support Tinto's Student Integration Theory, which proposes that persistence declines when students experience weakened academic integration during critical stages of progression. Berka and Marek (2021) reported similar patterns, demonstrating that attrition risk increases as academic expectations intensify and students experience progression barriers. The present findings extend existing scholarship by identifying institution-specific academic tipping points associated with mandatory programmatic divergence rather than general withdrawal behavior. The findings suggest that repeated academic difficulties during these stages increase the likelihood of mandatory programmatic divergence, including program shifting and discontinuation.

Differences in Academic Background and Institutional Retention Indicators

Table 6 presents the significant differences in academic background across socio-demographic variables. The findings showed significant differences in academic background by sex ($p = .007$), income level ($p = .001$), previous course ($p = .007$), and present course ($p = .048$). However, residence did not differ significantly ($p = .687$). The results indicate that academic preparation and attrition-related experiences vary according to economic status and program background. Students from different academic programs and income classifications showed different levels of vulnerability to mandatory programmatic divergence. The statistically significant values further imply that academic history and socio-economic conditions play important roles in shaping at-risk student profiles.

Table 6. *Differences in Academic Background by Selected Socio-demographic Variables*

Variable	Statistical Test	p	Interpretation
Sex	Mann-Whitney U	.007	Significant
Residence	Kruskal-Wallis H	.687	Not Significant
Income	Kruskal-Wallis H	.001	Significant
Previous Course	Kruskal-Wallis H	.007	Significant
Present Course	Kruskal-Wallis H	.048	Significant

Table 7 presents the significant differences in institutional retention indicators. The findings showed that institutional retention indicators differed significantly by year level ($p = .008$). Conversely, sex ($p = .336$), residence ($p = .727$), and income ($p = .224$) did not differ significantly. The significant result for year level suggests that institutional experiences vary across stages of academic progression. Students in higher academic levels may encounter different retention requirements, performance expectations, and academic demands that influence persistence and attrition outcomes. These findings reinforce the earlier observation that second- and third-year students represent critical periods requiring intensified institutional interventions.

Table 7. *Differences in Institutional Retention Indicators by Selected Socio-demographic Variables*

Variable	Statistical Test	p	Interpretation
Sex	Mann-Whitney U	.336	Not Significant
Residence	Kruskal-Wallis H	.727	Not Significant
Income	Kruskal-Wallis H	.224	Not Significant
Year Level	Kruskal-Wallis H	.008	Significant

Statistically Significant Factors Associated with At-Risk Student Profiles

Table 8. *Factors Associated with At-Risk Student Profiles*

Factor	M	SD	Interpretation
Academic Factors	3.42	0.88	Frequently Occurred
Financial Factors	3.08	1.18	Sometimes Occurred
Personal-Social Factors	3.46	0.65	Frequently Occurred
Tipping Point Factors	3.38	0.94	Sometimes Occurred

Table 8 presents the factors associated with at-risk student profiles. The findings showed that personal-social factors obtained the highest mean score ($M = 3.46$, $SD = 0.65$), followed by academic factors ($M = 3.42$, $SD = 0.88$), tipping point factors ($M = 3.38$, $SD = 0.94$), and financial factors ($M = 3.08$, $SD = 1.18$). The results indicate that academic, personal-social, financial, and tipping point factors were associated with attrition risk among students enrolled in licensure-based programs. Academic factors emerged as one of the strongest contributors to mandatory programmatic divergence, while personal-social concerns also demonstrated substantial influence. The mean scores suggest that attrition is multidimensional and cannot be explained by academic performance alone. Instead, the interaction among institutional conditions, financial concerns, academic demands, and personal-social experiences shapes student vulnerability.

The findings demonstrate that academic performance indicators alone do not fully explain student vulnerability. Rather, the interaction among academic, financial, institutional, and psychosocial dimensions influences student persistence outcomes. This observation supports Tinto (1993) and Bean (1980), who argued that attrition results from both internal academic experiences and external environmental pressures. Recent learning analytics literature likewise emphasizes multidimensional risk modeling using demographic, behavioral, and institutional indicators (Mduma et al., 2023; Goren et al., 2024; Dai et al., 2025). Unlike predictive studies primarily focused on machine learning classification, this study contributes empirical evidence using statistical profiling approaches to identify contextual attrition patterns within licensure-based retention environments.

The study contributes to the student attrition literature by extending existing retention and learning analytics research toward the context of mandatory programmatic divergence in licensure-based programs. Previous investigations primarily focused on predicting student withdrawals, classifying dropouts, and using machine learning to identify academically at-risk students. In contrast, the present study examined attrition through a multidimensional statistical perspective that integrated socio-demographic characteristics, academic background, institutional retention indicators, academic tipping points, and psychosocial indicators. The study further advances theoretical understanding by demonstrating that attrition-related vulnerability emerges from the interaction of academic integration, institutional experiences, environmental conditions, and self-efficacy

processes. Identifying second- and third-year academic tipping points provides empirical evidence for progression-stage vulnerability within retention-intensive programs.

From a practical perspective, the findings establish an evidence-based foundation for developing institutional Early Warning Systems and targeted intervention models. The proposed framework contributes to educational practice by providing measurable risk indicators that may guide academic monitoring, retention programs, psychosocial support initiatives, and data-driven student assistance mechanisms. At the policy level, the findings support transitioning from reactive attrition management to preventive, analytics-informed retention strategies in higher education institutions. The study further contributes to understanding the psychological dimensions of student attrition by demonstrating that persistence behaviors involve emotional adjustment, coping capacity, perceived competence, self-efficacy, and social adaptation processes. The prominence of personal-social factors suggests that attrition among licensure-based students extends beyond academic deficiencies and reflects broader psychological experiences affecting persistence and academic transitions.

The study utilized a descriptive quantitative design based on institutional records and cross-sectional survey responses obtained from one private higher education institution. Consequently, the study could not establish causal relationships, and findings may have limited generalizability across institutions with different retention systems and program structures. The study also focused on selected licensure-based programs and did not include longitudinal monitoring or predictive modeling. The study relied partly on self-reported survey responses, which may be subject to social desirability, response, or recall bias. Respondents may have unintentionally underreported or overreported experiences related to academic challenges, financial concerns, and personal-social factors despite assurances of anonymity and confidentiality. Future studies may expand institutional coverage and employ longitudinal analytics to strengthen predictive validity.

Conclusion

A complex interplay of academic, institutional, financial, and personal factors shapes student attrition and mandatory programmatic divergence in licensure-based programs. Risk is not determined by academic performance alone, as institutional experiences, socioeconomic status, and psychosocial circumstances also matter. Vulnerability increases as students advance through more challenging stages of their programs. Attrition is best addressed as an institutional challenge requiring proactive, student-centered interventions. Early monitoring of academic, institutional, and personal risk indicators can help prevent withdrawal, particularly in demanding programs. Strengthening support systems and using risk indicators to design targeted interventions before students reach critical points can improve student retention. Data-driven, preventive strategies, including academic, financial, and wellness support, are essential for promoting student persistence and institutional outcomes.

Shifting to data-driven, preventive strategies, including academic, financial, and wellness support, can improve student persistence and institutional outcomes. While this study did not develop an Early Warning System, the findings provide a foundation for identifying and supporting at-risk students in the future. Institutions can use these insights to guide timely, coordinated interventions. This research expands the understanding of attrition in licensure-based programs by introducing mandatory programmatic divergence and identifying new risk patterns. Future studies should use broader methods, additional variables, and advanced analytics to deepen understanding and improve the generalizability of findings. By introducing mandatory programmatic divergence, the study identifies institution-specific attrition factors and key risk indicators through statistical profiling. Future research should use broader methods, additional variables, and advanced analytics to deepen understanding and improve the generalizability of findings. In sum, this study offers an evidence-based foundation for more responsive and preventive retention initiatives in higher education licensure-based programs.

Contributions of Authors

Author 1: Conceptualization, data gathering, data analysis, interpretation of results, and manuscript preparation.
Author 2: Conceptualization, research supervision, methodological guidance, and critical review of the manuscript.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the conduct, authorship, or publication of this study.

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