APPLICATION OF STATISTICAL PROCESS CONTROL AND ISHIKAWA ANALYSIS IN MONITORING STUDENT AT RISK RATES IN SCIENCE AND MATHEMATICS EDUCATION PROGRAMS

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ABSTRACT- *This retrospective quality-monitoring study applied Statistical Process Control (SPC) and Ishikawa analysis to semester-level student at-risk records in the Science Education and Mathematics Education programs of the University of Science and Technology of Southern Philippines. Complete aggregate records for six semesters from Academic Year (AY) 2023–2024 through AY 2025–2026 were analyzed using p-charts with subgroup-specific three-sigma control limits. Science Education recorded 60 at-risk cases across 673 student-enrollments (weighted mean = 8.92%), whereas Mathematics Education recorded 34 cases across 270 student-enrollments (weighted mean = 12.59%). In both programs, the 1st Semester of AY 2024–2025 exceeded the upper control limit, indicating special-cause increases (Science: $p = 0.2389$, $UCL = 0.1696$; Mathematics: $p = 0.4146$, $UCL = 0.2814$). The zero rates in the 1st Semester of AY 2023–2024 also fell below the lower control limits and therefore require verification as unusually favorable outcomes or possible classification/data-quality effects. The Ishikawa map organized causes into student, instructional, curriculum, resource, institutional-support, and external domains. The findings support semester-based monitoring and targeted investigation, but the six-period series and unvalidated root-cause categories require cautious interpretation. SPC should be used as an early-warning and quality-improvement tool rather than as proof of causation.*

Keywords- Academic risk, Higher education, Ishikawa diagram, P-chart; statistical process control, Student retention

INTRODUCTION

Student retention is a central quality concern in higher education because withdrawal, delayed progression, and repeated failure affect students, programs, and institutional resources. Reviews of university dropout show that risk is not explained by a single variable; academic preparation, socioeconomic conditions, motivation, institutional organization, and the timing of students' experiences interact across the study pathway [1–3]. First-year and gateway-course performance is especially important because early academic, social, and motivational experiences are associated with subsequent success [2].

Science, technology, engineering, and mathematics (STEM)-related programs are particularly sensitive to foundational knowledge and sequential prerequisites. Learning-analytics studies demonstrate that early course behavior and performance can identify students who may require support before failure occurs [4–8]. However, prediction and retrospective reporting do not by themselves provide a process-monitoring mechanism. A program chair may know the annual percentage of at-risk students but still lack an objective way to determine whether a semester represents routine fluctuation or an unusual process shift.

Statistical Process Control (SPC) addresses this problem by placing outcomes in time order and distinguishing common-cause variation from special-cause signals [10–12]. For a proportion such as the number of students classified as at risk divided by total enrollment, the p-chart is appropriate when subgroup sizes vary. Unlike a conventional hypothesis test, a control chart evaluates process behavior against limits estimated from the process itself; a point outside a control limit is a signal for investigation rather than proof of a particular cause [11]. Educational applications of SPC indicate that control charts can support objective review of program performance and continuous improvement [10].

SPC identifies when investigation is needed but does not diagnose why a signal occurred. Ishikawa's cause-and-effect method provides a structured way to organize possible contributors across multiple domains [13]. In education, those domains may include student preparation, teaching and assessment, curriculum sequencing, learning resources, institutional support, and external pressures. studies show that academic performance and intervention outcomes can be related to instructional quality, monitoring, motivation, institutional review programs, learning technologies, and structured support [14–19].

The present study therefore examined aggregate at-risk rates in the Science Education and Mathematics Education programs at USTP across six semesters. It aimed to (1) compute semester-level at-risk rates, (2) construct program-specific p-charts, (3) identify special-cause signals, (4) organize plausible causes using an Ishikawa framework, and (5) propose an institutional response process. The study contributes a simple monitoring approach that can be implemented with routinely available academic records while recognizing that a diagnostic diagram must be validated with program evidence before causal conclusions are made.

MATERIALS AND METHODS

Research Design and Data Source

The study used a retrospective descriptive quality-monitoring design. Aggregate secondary records were obtained from the University of Science and Technology of Southern Philippines for the Science Education and Mathematics Education programs. The observation window covered six consecutive semesters from the 1st Semester of AY 2023–

2024 through the 2nd Semester of AY 2025–2026. Total enumeration was used; consequently, the analysis covered every student-enrollment appearing in the supplied semester records rather than a sample.

Operational Definition and Data Preparation

The numerator for each semester was the number of students recorded by the institution as academically at risk, while the denominator was total program enrollment for the same semester. The institutional designation may include indicators such as failing grades, probation, repeated courses, shifting, or discontinuation, as reflected in official records. No personally identifiable information was analyzed. Before operational deployment, the institution should maintain one documented classification rule across semesters because changes in screening criteria can themselves produce control-chart signals.

Statistical Process Control

For semester i, the observed proportion was calculated as $p_i = x_i/n_i$, where x_i is the number of at-risk students and n_i is total enrollment. The weighted center line was computed as $\bar{p} = \Sigma x_i/\Sigma n_i$. Because enrollment varied by semester, control limits were calculated separately for each subgroup: $UCL_i = \min[1, \bar{p} + 3\sqrt{\bar{p}(1-\bar{p})/n_i}]$ and $LCL_i = \max[0, \bar{p} - 3\sqrt{\bar{p}(1-\bar{p})/n_i}]$. A point above the UCL or below the LCL was treated as a special-cause signal requiring investigation. The terms "in control" and "out of control" refer to statistical process behavior and do not imply acceptable or unacceptable educational performance [11, 12].

Only six subgroups were available per program. Therefore, the analysis focused on points beyond the three-sigma limits and did not apply extended run rules that ordinarily require longer sequences.

Ishikawa Diagnostic Procedure

For semesters with special-cause signals, a cause-and-effect framework was developed using six domains: student factors, faculty/instruction, curriculum, learning resources, institutional support, and external factors. The categories were informed by the higher-education and local literature [1–9, 14–20]. Since the available dataset contained no interviews, course-level failure distributions, advising records, or student-level covariates, the listed causes are diagnostic hypotheses.

Ethical Considerations

Institutional permission was secured for the use of records. Data were handled confidentially, and no names, student numbers, or identifiable profiles were included in the analysis or reporting. The study presents program-level monitoring results and does not rank or identify individual students or faculty members.

RESULTS

Table 1: Science Education Enrollment and At-Risk Rates

Period	Enrolled	At risk	Rate (%)
1S 23–24	146	0	0.00
2S 23–24	140	6	4.29
1S 24–25	113	27	23.89
2S 24–25	97	16	16.49
1S 25–26	91	6	6.59
2S 25–26	86	5	5.81

Note. Rates use semester-level student-enrollment a student may appear in more than one period.

Table 2

Mathematics Education Enrollment and At-Risk Rates

Period	Enrolled	At risk	Rate (%)
1S 23–24	67	0	0.00
2S 23–24	58	9	15.52
1S 24–25	41	17	41.46
2S 24–25	37	4	10.81
1S 25–26	34	3	8.82
2S 25–26	33	1	3.03

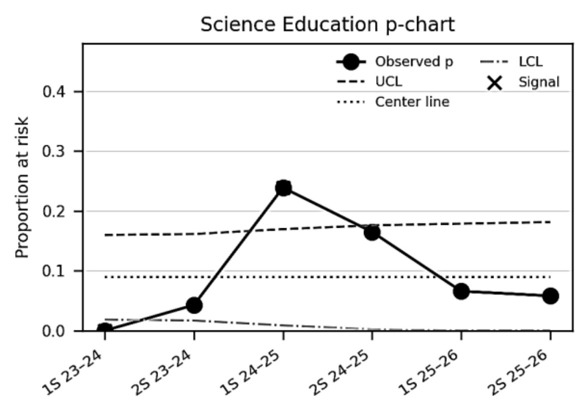
Note. Rates use semester-level student-enrollments; a student may appear in more than one period.

Science Education recorded 60 at-risk cases across 673 student-enrollments (weighted mean = 8.92%). Mathematics Education recorded 34 cases across 270 student-enrollments (weighted mean = 12.59%). Both programs reached their highest observed rate in 1S 24–25: 23.89% in Science Education and 41.46% in Mathematics Education.

Table 3: Science Education p-Chart Parameters

Period	p_i	UCL_i	CL	LCL_i	Signal
1S 23–24	0.0000	0.1599	0.0892	0.0184	Low
2S 23–24	0.0429	0.1614	0.0892	0.0169	None
1S 24–25	0.2389	0.1696	0.0892	0.0087	High
2S 24–25	0.1649	0.1760	0.0892	0.0024	None
1S 25–26	0.0659	0.1788	0.0892	0.0000	None
2S 25–26	0.0581	0.1813	0.0892	0.0000	None

Note. CL = center line; UCL/LCL = upper/lower control limits;



Low/High = special-cause signal.

Figure 1 Science Education p-Chart

Note. *Cross markers identify observations outside the three-sigma limits.*

Science Education had a below-LCL zero rate in 1S 23–24 (LCL = 0.0184) and an above-UCL rate of 0.2389 in 1S 24–25 (UCL = 0.1696). The other four periods were within their subgroup-specific limits.

Table 4: Mathematics Education p-Chart Parameters

Period	p_i	UCL_i	CL	LCL_i	Signal
1S 23–24	0.0000	0.2475	0.1259	0.0043	Low
2S 23–24	0.1552	0.2566	0.1259	0.0000	None
1S 24–25	0.4146	0.2814	0.1259	0.0000	High
2S 24–25	0.1081	0.2896	0.1259	0.0000	None
1S 25–26	0.0882	0.2966	0.1259	0.0000	None
2S 25–26	0.0303	0.2992	0.1259	0.0000	None

Note. Negative lower limits were truncated to zero because proportions cannot be negative.

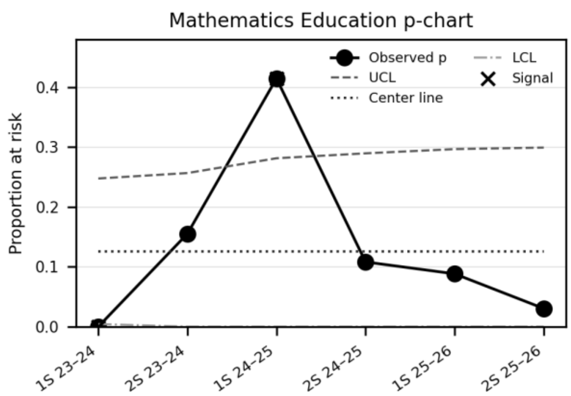


Figure 2: Mathematics Education p-Chart

Note. Cross markers identify observations outside the three-sigma limits.

Mathematics Education showed the same timing: a below-LCL zero rate in 1S 23–24 (LCL = 0.0043) and an above-UCL rate of 0.4146 in 1S 24–25 (UCL = 0.2814). The simultaneous high signals identify 1S 24–25 as the principal period for cross-program investigation.

Table 5: Special-Cause Signals and Follow-Up

Program/period	Signal	Priority follow-up
Science, 1S 23–24	Below LCL	Verify record completeness and classification consistency; document favorable practices if confirmed.
Science, 1S 24–25	Above UCL	Review high-failure courses, prerequisites, assessments, attendance, advising, and support use.
Mathematics, 1S 23–24	Below LCL	Verify record completeness and classification consistency; document favorable practices if confirmed.
Mathematics, 1S 24–25	Above UCL	Conduct a cross-program review of curriculum load, instruction, and support.

Table 6: Ishikawa Cause Domains

Domain	Plausible mechanisms requiring validation
Student factors	Weak prerequisite knowledge; low motivation; poor study habits; absenteeism; non-STEM preparation.
Faculty / instruction	Teaching-learning misalignment; assessment difficulty; inconsistent delivery; limited feedback.
Curriculum	Prerequisite difficulty; congested loads; sequencing or alignment problems; theory-practice gaps.
Learning resources	Insufficient laboratories, equipment, materials, library resources, or digital access.
Institutional support	Limited tutoring, remediation, advising, mentoring, monitoring, or delayed intervention.
External factors	Financial hardship, family obligations, health concerns, transportation, and social pressures.

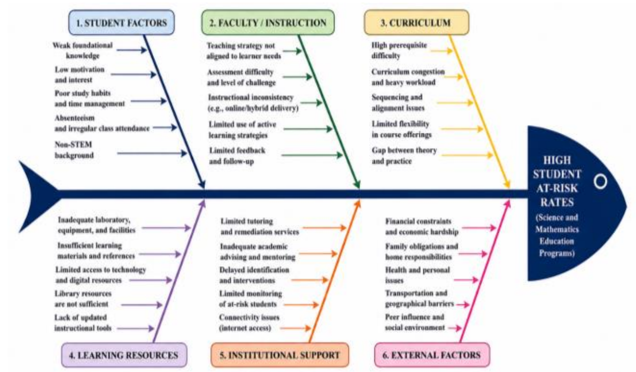


Figure 3: Ishikawa Map of Root Cause Domains

DISCUSSION

Baseline Risk and Temporal Variation

The weighted center line was higher in Mathematics Education (12.59%) than in Science Education (8.92%). This descriptive difference indicates a higher average proportion of at-risk student-enrollments in Mathematics during the observed period, but it should not be interpreted as a causal program comparison. The programs had different enrollment sizes, course structures, and potentially different student characteristics. Reviews of first-year success and dropout similarly emphasize that academic outcomes are influenced by multiple academic, motivational, and contextual domains [1–3].

Both programs produced an above-UCL signal in the 1st Semester of AY 2024–2025. The shared timing raises a reasonable hypothesis that cross-program or institution-level conditions contributed to the increase. Possible explanations include changes in curriculum sequencing, unusually difficult gateway courses, assessment calibration, learning-resource access, or the timing and capacity of support services. Nevertheless, the chart cannot identify which explanation is correct. Course-level and stakeholder evidence is necessary before attributing the signal to any specific factor.

Interpretation of the Zero-Rate Signals

Below-LCL signals in the 1st Semester of AY 2023–2024 because both programs recorded zero students at risk. This result is statistically unusual relative to the weighted baselines. A zero may represent genuinely strong performance, but it may also arise when screening procedures, documentation practices, or the definition of at-risk status differ from later semesters. Quality monitoring therefore requires a data-verification step. If the records are complete and the definition was consistent, the institution may identify and preserve the practices associated with that favorable semester.

Value of SPC for Educational Monitoring

The findings illustrate the advantage of SPC over a simple table of percentages. Descriptive reports show that rates changed; the p-chart indicates which changes are unlikely to be explained by the estimated common-cause variation of the monitored process. Prior work has shown that SPC can be adapted to academic-program performance and can focus institutional attention on periods requiring investigation [10]. Early-warning research likewise supports the use of timely, interpretable monitoring systems to connect detection with support [4–8].

Root-Cause Domains and Local Evidence

The Ishikawa framework treated academic risk as a system outcome rather than solely a student deficit. Student preparation and motivation matter, but teaching, assessment, curriculum, resources, and institutional response may either reduce or intensify risk. A srudy reported the use of targeted learning-camp support for struggling students [14]; emphasized the relationship of professional instructional practices and mathematics performance [15] highlighted the need to evaluate institutional review interventions rather than assume their effectiveness [16].

Technology-supported learning and motivation are also relevant but should be matched to the identified need. improved performance after a gamified learning-management intervention in Physical Science [17], while a study underscored the role of orientation, motivation, and support in academic performance [18. 21] TVET-based instructional materials incorporating hands-on activities, digital simulations, and collaborative tasks produced greater learning gains and higher critical thinking, creativity, collaboration, and communication scores than conventional lecture-discussion instruction. Longitudinal performance records can inform curriculum review and intervention planning in teacher education [19].

Implications for Institutional Action

The 1st Semester of AY 2024–2025 may be treated as the priority investigation period. A cross-program review can begin with course-level failure and withdrawal distributions, particularly in prerequisite and gateway courses. This should be followed by a review of assessment design, teaching schedules, laboratory and digital access, advising contacts, tutoring participation, and student-reported barriers. Academic stress and external pressures may also contribute to reduced performance and persistence [20], but collection of such information must be confidential and ethically managed.

CONCLUSION

SPC revealed that student at-risk rates in the two programs were not characterized solely by routine semester-to-semester variation. Science Education had a weighted average at-risk rate of 8.92%, and Mathematics Education had a weighted average of 12.59%. Both programs showed an above-UCL signal in the 1st Semester of AY 2024–2025, identifying a common high-risk period for institutional investigation. Both also showed below-LCL zero rates in the 1st Semester of AY 2023–2024, which should be verified as genuine improvement or a possible data-classification effect. The Ishikawa framework causes but does not establish them. Accordingly, the main contribution of the study is an operational monitoring-and-inquiry framework: SPC indicates when to investigate, while validated root-cause analysis determines what action is warranted.

RECOMMENDATIONS

- Standardize and document one operational definition of "student at risk," including the timing, responsible office, and evidence required for classification.
- Maintain semester-level p-charts for each program and require a documented verification and root-cause review whenever a point crosses a control limit.
- Audit the 1st Semester of AY 2024–2025 at course level, including prerequisite chains, failure and repeat rates, assessment distributions, attendance, advising, tutoring, and resource access.
- Link identified needs to targeted interventions such as bridge activities, tutoring, mentoring, assessment review, curriculum sequencing changes, or financial and psychosocial referrals, then monitor subsequent semesters for sustained improvement.
- Expand the time series and consider alternative charts or models if overdispersion, serial dependence, or changing risk definitions are detected.

REFERENCES

[1] Aina, C., Baici, E., Casalone, G. and Pastore, F., "The determinants of university dropout: A review of the socio-economic literature," *Socio-Economic Planning Sciences*, **79**: Art. no. 101102, doi: 10.1016/j.seps.2021.101102 (2022).

[2] van der Zanden, P. J. A. C., Denessen, E., Cillessen, A. H. N. and Meijer, P. C., "Domains and predictors of first-year student success: A systematic review," *Educational Research Review*, **23**: 57–77, doi: 10.1016/j.edurev.2018.01.001 (2018).

[3] Wild, S. and Schulze Heuling, L., "Student dropout and retention: An event history analysis among students in cooperative higher education," *International Journal of Educational Research*, **104**: Art. no. 101687, doi: 10.1016/j.ijer.2020.101687 (2020).

[4] Bernacki, M. L., Chavez, M. M. and Uesbeck, P. M., "Predicting achievement and providing support before STEM majors begin to fail," *Computers & Education*, **158**: Art. no. 103999, doi: 10.1016/j.compedu.2020.103999 (2020).

[5] Macfadyen, L. P. and Dawson, S., "Mining LMS data to develop an 'early warning system' for educators: A proof of concept," *Computers & Education*, **54**(2): 588–599, doi: 10.1016/j.compedu.2009.09.008 (2010).

[6] Atif, A., Richards, D., Liu, D. and Bilgin, A., "Perceived benefits and barriers of a prototype early alert system to detect engagement and support 'at-risk' students: The teacher perspective," *Computers & Education*, **156**: Art. no. 103954, doi: 10.1016/j.compedu.2020.103954 (2020).

[7] Vaarma, M. and Li, H., “Predicting student dropouts with machine learning: An empirical study in Finnish higher education,” *Technology in Society*, **76**: Art. no. 102474, doi: 10.1016/j.techsoc.2024.102474 (2024).

[8] Lu, O. H. T., Huang, A. Y. Q. and Yang, S. J. H., “Impact of teachers’ grading policy on the identification of at-risk students in learning analytics,” *Computers & Education*, **163**: Art. no. 104109, doi: 10.1016/j.compedu.2020.104109 (2021).

[9] Tinto, V., “Through the eyes of students,” *Journal of College Student Retention: Research, Theory & Practice*, **19**(3): 254–269, doi: 10.1177/1521025115621917 (2017).

[10] Gessa, A., Marin, E. and Sancha, P., “A practical application of statistical process control to evaluate the performance rate of academic programmes: Implications and suggestions,” *Quality Assurance in Education*, **30**(4): 571–588, doi: 10.1108/QAE-03-2022-0065 (2022).

[11] Montgomery, D. C., *Introduction to Statistical Quality Control*, 8th ed., Wiley, Hoboken, NJ, USA (2019).

[12] Benneyan, J. C., Lloyd, R. C. and Plsek, P. E., “Statistical process control as a tool for research and healthcare improvement,” *Quality and Safety in Health Care*, **12**(6): 458–464, doi: 10.1136/qhc.12.6.458 (2003).

[13] Ishikawa, K., *Guide to Quality Control*, 2nd rev. ed., Asian Productivity Organization, Tokyo, Japan (1986).

[14] Mapue, J. O., “Exploring the National Learning Camp and academic performance among student participants in Department of Education Dumaguete City Division,” *Sci-Int. (Lahore)*, **37**(1): 143–152 (2025).

[15] Badiang, C. H., “Personal and professional attributes of teachers in relation to students’ academic performance in mathematics,” *Sci. Int. (Lahore)*, **35**(4): 517–520 (2023).

[16] Dayadaya, R. M. N. and Sermona, N. L. D., “Graduates’ perspectives of the institutional intervention for the improvement of the Licensure Examination for Teachers’ performance,” *Sci-Int. (Lahore)*, **36**(3): 343–345 (2024).

[17] Cajilla, K. Z. and Bug-os, M. A. A. C., “Students’ perceived satisfaction and academic performance utilizing a gamified learning management system for senior high school,” *Sci. Int. (Lahore)*, **34**(6): 639–645 (2022).

[18] Capilitan, F. T., Jr., “Investigating the body mass index and academic performance among the technology education students in a state university in Northern Mindanao: A mixed-method research design,” *Sci. Int. (Lahore)*, **34**(2): 63–67 (2022).

[19] Aberin, S. P., Fajardo, M. T. M. and Sermona, N. L. D., “An analysis of the five-year performance of BSED-TLE graduates in the Licensure Examination for Teachers,” *Sci. Int. (Lahore)*, **31**(2): 213–219 (2019).

[20] Iqra, “A systematic review of academic stress intended to improve the educational journey of learners,” *Methods in Psychology*, **11**: Art. no. 100163, doi: 10.1016/j.metip.2024.100163 (2024).

[21] Flores, J. P., “Enhancing 21st-Century Competencies Through TVET-Based Instructional Materials in Teacher Education: A Quasi-Experimental Research,” Science International (Lahore), **38**(4): 57–62 (2026).