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Academic withdrawal in engineering: an investigation of scenarios and root causes

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Abstract: University students drop some courses for personal, institutional, and other reasons. Course withdrawal affects students' progress and sometimes leads to complete abandonment. This study aimed to develop the subject-drop scenario in engineering disciplines, identify root causes linked to personal, course-related, and institutional and provide preventive measures. Secondary data from eight semesters over nine years involving 450 students' published results were analyzed. To identify withdrawal causes, 319 students who dropped at least one course were interviewed through a questionnaire. Descriptive and inferential statistical analysis was used to build a scenario and determine the causes and effects of course drops. Based on the results and extensive literature review, a conceptual framework was developed and tested with PLS SEM 4.0. According to findings, 83% of students failed at least one subject, and 8% dropped more than 20 courses over the academic year. Academic withdrawal or subject drop is prevalent for 30% of first-year students, increasing to 50% of second-year students and gradually decreasing from the third year. All three developed hypotheses, and the developed model was tested and validated.

Keywords**:** Subject-drop; Root cause; Relative important index; Independent study; Academic commitment.

Introduction

Engineering education in any part of the world requires systematic continuation of the study. The academic curriculum of engineering is designed in such a systematic manner that the majority of the courses rely on the previous courses. If one course is not being continued, it would hamper the next level course. Students of engineering discipline need to be very keen and effective in their education to complete the degree within the specified period. Failure to complete any course or subject within the prescribed duration is termed withdrawal in academic terms. The withdrawal of the courses is an area of research that needs in-depth analysis to build the scenario and identify the root causes.

Dropout is a multi-attribute phenomenon as the reason behind the dropout comprises the interaction between various personal and contextual factors. When a student drops a single course, he withdraws several subjects later due to increased stress and course loads. Subject drops might cause some students to leave the university, suspend enrollment, or lengthen their study period. Students who leave university before obtaining their degree or withdraw from several courses may need help financially and academically. The extended students' graduation duration causes several personal problems, and the institution also faces some academic and administrative issues with those students. Students need additional expenditure to complete the failed/withdrawn courses. The quality of learning for the students prone to course drop is seriously compromised. This phenomenon concerns engineering students who must enter the job market quickly. Also, their higher study is at stake due to this. Hence, students and their families and institutions suffer in the long run.

Usually, dropout is defined as the dismissal of a particular program (Lassibille and Navarro Gómez, 2008). During the study period, dropouts may include students who registered but did not turn up, completed coursework or did not renew their enrolment for the following year. Sometimes, students fail to achieve a cut-off point for consecutive semesters; in that case, they may take a break from studying and return later (Saele, 2016). Although the complete failure at the tertiary level is not alarming, Course withdrawal becomes a major issue at this level.

At the tertiary level, the dropout phenomenon is comparatively less explored, more complicated, and has multi-dimensional attitudes that depend on the country's institutional education system, culture, and socioeconomic context. Studying the dropout scenario in a particular discipline is necessary because prior knowledge about the dropout may help the university's policymakers concentrate more on the weaker students and prevent them from subject withdrawal. At the same time, students can be more attentive from the beginning to avoid course drops, knowing the relevant feedback from the institution.

In this study, the case has been studied to develop the scenario of course dropout along with underlying root causes. A framework has been developed and testified to link the different reasons with the number of drops. This paper presents the findings that analyzed the data from nine consecutive programs, each consisting of eight successive semesters. Altogether, semester-wise results of 450 students have been analyzed to build the scenario, and feedback on the causes of the drop has been collected from 319 students of three engineering disciplines graduates of a public university.

Background

Most of the previous research on students, who dropout of school and college concluded that several attributes are responsible for dropout. Rumberger and Russell (2012), while studying high school student dropout ratio, divided the precursor of dropout into two groups: institutional and individual factors. Chandra and Nandhini (2010) concluded a relationship between failed courses and provided suggestions regarding causes. Researchers showed several contradictory natures of dropouts. The previous researcher explained the dropout phenomenon with repetitive variables associated with student psychological characteristics such as parent's education (Araque et al., 2009), socioeconomic background (Vignoles et al., 2009), and general and educational characteristics. In a study, the Bayesian classification method was applied to 17 causes and found that causes like students' accommodation, learning method, mother's qualification, students' other practices, family income, and student's family status were highly associated with the student's educational performance (Pal, 2012). In contrast, Cingano and Cipollone (2007) claim that guardian education level and local conditions do not affect the complete dropout.

A study in Brazilian Federal University (Costa et al., 2018) in business discipline showed that the number of semesters, student grade, gender, and failure or dropout influence the degree completion time and the dropout risk. A case study in Italian universities showed that gender significantly influences dropouts (Rosário et al., 2014). Casanova et al. (2018) showed that females are more prone to drop out than male students; also, they have a different cause behind complete termination from the program. For instance, male students appear to have a higher dropout rate because they devote less time to academic pursuits. In contrast, female students who dropout tend to have difficulty integrating into society (Rosário et al., 2014).

While exploring the determinants of success in engineering education, Wang et al. (2022) found that female students demonstrate more positive outcomes than their male peers. Costa et al. (2018) found that age, marital status, race, and high school background did not affect the completion time and dropout. On the contrary, Vignoles et al. (2009) found that white students are more likely to dropout than ethnic minority students, meaning race significantly influences dropout. In another study, Beaumont-Walters et al. (2001) tried to connect different social and economic factors with student's performance levels. The relationship between students' performance and school type was statistically significant, while there was a weak relationship between student type, grade level, socioeconomic background, and performance. In another study, Perchinunno et al. (2019) suggested that the decision to dropout of university could be influenced by factors such as inadequate preparation, inadequate knowledge of the environment and poor understanding of efficient study strategies.

Some researchers tried to predict the early intention of students to dropout using different models. Yujiao et al. (2023) suggested a dropout prediction model to identify college students in danger of dropping out, allowing for early intervention and support to prevent dropout. Some researchers focused on first-year students and determined the cause for their decision to dropout. In some cases, students might not be able to get their preferred course due to required cut-off marks and sometimes choose the wrong course due to lack of information, guidance, or other reasons (Rodríguez-Gómez et al. 2012), which eventually leads them to withdraw (Vignoles et al., 2009). Research of longitudinal data set on student enrolments showed that early dropout is strongly related to the mandatory first-year courses taken by university students; after that, a strong academic performance was proven to be the critical element to continuing at that University (Montmarquette et al., 2001). Also, difficulty coping with the learning process results in lower academic achievement, influencing the dropout decision (Casanova et al., 2021). Paura et al. (2014) identified that inadequate secondary school knowledge and lack of motivation for engineering study are the main reasons students leave university during their first academic year. The biggest challenge for institutions is to predict students' behavior (Ramasubramanian et al., 2009), and result evaluation is an essential tool to control and monitor learning quality (Sun, 2010). Stinebrickner and Stinebrickner (2012) used unique longitudinal data to indicate that departure from school arises when students know about their academic performance. They also identified from the simulation that dropouts between the first and second years would be reduced by 40% if students were unaware of their academic talent. Boero et al. (2005), in their study of post-reform Italian universities, found that differences in students' prior educational background and performance have considerable effects on their withdrawal and progression probabilities. In a business school, researchers identified three predictors: student grade performance, program evaluation in the first semester, and financial difficulties associated with future dropouts (Mangum et al. 2005). Also, some students have weak mathematical knowledge from their previous studies. Students frequently have a structured view of mathematics, emphasizing symbols, rules, and procedures, which limits their capacity to apply mathematical principles to engineering problem-solving scenarios (Charalambides et al., 2023). Llauró et al. (2023) underline the significance of discovering personal indicators in the student's profile that suggest a higher chance of dropping out early.

In the case of engineering students, teaching quality and modification of curriculum plays a vital role in reducing course drop (Litzler & Young, 2012). Engineering students with less self-efficacy and academic confidence are more prone to dropout. The student-faculty relationship and peer relationship enhance self-efficacy. Academic performance depends on a student's past knowledge, educational environment, motivation level, etc. (Vogt, 2008). Shankar et al. (2016) examined students' performance at higher education levels using K-mean clustering and suggested solutions to improve students' performance. Pal (2012) used data mining to reduce engineering students' dropout rates in another study. Lara-Cabrera et al. (2023) investigated using real and virtual badges as a gamification strategy to increase student performance and decrease dropout rates in STEM higher education.

The previous researchers mainly concentrated on complete dropouts from the program, identified several factors linked to the high dropout rate in higher education institutes, and provided various suggestions related to their field of study to reduce dropouts. However, this study focuses on the course dropout cause that leads the student to drop from the program or an extended period of student life or to complete the program within a stipulated duration but to compromise semester-wise regular learning.

The novelty of this research is the development of the scenario of subject dropout by engineering students at the university level. The root causes of academic withdrawal are identified, and a framework has been developed and testified to link the different reasons with the number of drops. The findings of this paper will provide an overall scenario about the dropout cause, underlying root causes, some immediate causal effects, and some preventive measures. The research outcomes would add substantial value to the literature and explore new awareness for researchers and policymakers in engineering higher education.

Methodology

The research was conducted with an applied multimethod research approach. Secondary data have been collected from case organizations for ten successive years, from 2007 to 2016, to build up existing scenarios. Henceforth, the data regarding the course withdrawal of nine consecutive batches are collected from the earlier records (published results). The course drop scenario is analyzed using Excel to identify the percentage of regular students, variation of withdrawal rate to semester progress, vulnerable courses in drop occurrence, and the relation between students and the number of dropped courses over semesters.

A test survey was conducted to search for relevant questions regarding course drop. The preliminary questionnaire was developed, and interviews were conducted to observe the responses. The responses were good. The experts further verified the questionnaire. The questionnaire consists of 23 causes under three immediate factors, such as personal cause (PC), course consideration (CC), and institutional consideration (IC), that influence the students to withdraw. A simple random sampling method was used to select the participants. Direct interviews and google forms were used to collect data from selected department students. The students of the different batches in three engineering departments who dropped at least one course in their study period were interviewed. The demographic data summaries are given in Table 1. The questions regarding causes behind course drop were formed based on a Likert scale in the order of 5 getting the highest priority to 1 getting the lowest priority. The collected data was sorted and analyzed using the statistical package for social science SPSS (version 26). Descriptive statistics, inferential statistics, data mining, and root cause analysis were done. The results obtained from the collected data are interpreted to draw a valid conclusion.

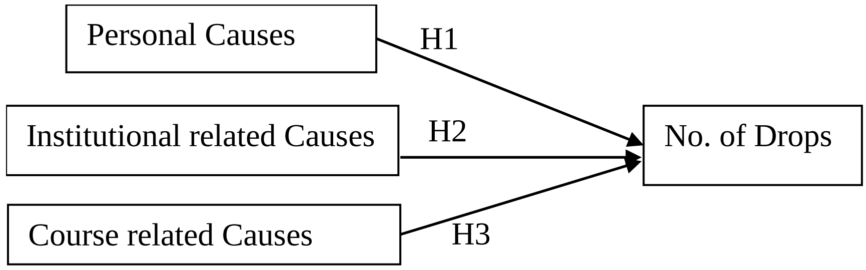
Table 1 Demographic data summary to conduct the survey

Demographic variables	**Category**	**Percentage**
Gender	Male	88.6%
	Female	11.4%
Ages	<20	20.7%
	20-24	55.0%
	25-30	21.0%
	>30	2.4%
Batches	Batch 1	8.0%
	Batch 2	10.0%
	Batch 3	10.5%
	Batch 4	11.0%
	Batch 5	14.0%
	Batch 6	13.0%
	Batch 7	12.0%
	Batch 8	11.5%
	Batch 9	10.5%

Conceptual Framework

A conceptual framework is a structured theoretical model that provides a foundation for understanding, analyzing, and interpreting complicated occurrences or relationships within a certain field of study. It acts as a blueprint or roadmap for researchers and scholars, assisting them in organizing their thoughts, guiding their research, and drawing relevant findings. The findings from the analysis suggest that three immediate causes, personal causes, institutional causes, and course-related causes, contribute to course dropout. Based on the relation or path, a conceptual framework has been developed. The conceptual framework considering the relation between immediate causes and no. of course dropout is shown in Figure 1. Personal causes (PC) constitute 11 components, while institutional-related causes (IC) are categorized into four components, and course-related causes (CC) are a combination of eight factors. The details of the categories of PC, IC, and CC are shown in Table 8.

Figure 1 Conceptual Framework



Hypothesis 1

Personal factors have a significant effect on course dropout rates. In a study, Aldowah et al. (2020) identified that personal causes, such as the socioeconomic condition of parents, significantly influence students' dropout rates. In different studies, some researchers suggested that students' low social interaction/communication may trigger their intention to dropout of the learning activity because active interaction with the content, peers, and instructors synchronously or asynchronously can help deepen their understanding of the learning topic (Lu et al., 2017; Moore, 1989; Whitehill et al., 2017; York and Richardson, 2012). Considering the influence of personal causes on course dropout, the first hypothesis of this study has been developed.

H1: Personal causes influence course withdrawal decision.

Hypothesis 2

Institutional facilities and learning environments play another vital role in students' motivation. Lack of suitable facilities and less interaction with peers and instructors deemed their enthusiasm and resulted in dropout. In a study, researchers emphasized academic satisfaction in students' performance (Long and Noor., 2023). Some findings support what other authors have discovered: the primary causes were poor teaching standards and bad interactions between students and instructors (Tayebi et al., 2021). Another hypothesis has been developed based on the importance of this cause of course dropout.

H2: Institutional causes influence course drop decision.

Hypothesis 3

Students who enter engineering education after completing their higher secondary degree find adjusting to the new curriculum and educational system difficult. Some students also struggle to relate their previous knowledge to the current program. Another important aspect consistently seen in students is fear of mathematical subjects inseparable from engineering. Also, the inadequacy of course-related material and opaque lecture delivery construct fear in students about the respective subject and eventually results in course dropout. This finding influenced the study to adopt its last hypothesis.

H3: Course-related causes influence course withdrawal decisions.

Data Analysis and Result

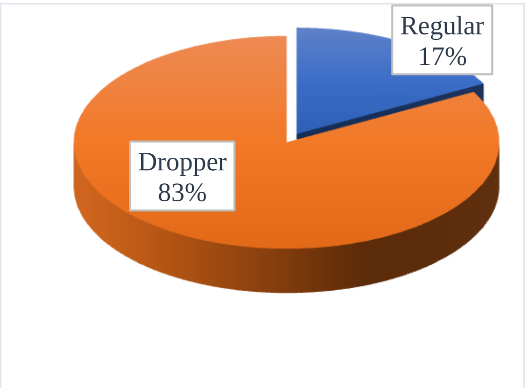
Percentage of total regular and dropper students

Course withdrawal refers to failing a course or not registering for it during the regular semester and taking it the following semester. The student who drops any subject in any semester is called a dropper. On average, 50 students are admitted to the undergraduate program every batch. However, due to the admission process and re-admission or admission cancellation, the total number of students varies in each batch. This research studied nine consecutive batches. Table 2 shows the number of students in each batch enrolled in the first semester as regular students.

Table 2 Total Number of Students Present in Each Batch.

Batch	Total Student	Pass without Drop	Pass without a drop (%)
Batch1	46	11	24%
Batch2	51	8	16%
Batch3	47	6	13%
Batch4	52	5	10%
Batch5	48	9	19%
Batch6	53	14	26%
Batch7	57	10	18%
Batch8	50	6	12%
Batch9	51	9	18%
Total	455	78	17.1%

Figure 2 Percentage of All Regular Students and Dropouts



By monitoring nine consecutive batches, it is clear that only 17% of students in each batch completed all semesters without a single course drop (Figure 2).

Table 3 The Number of students attending each semester's exams in every batch.

Batch	Semester							
	1st	2nd	3rd	4th	5th	6th	7th	8th
Batch1	46	45	44	43	43	43	43	43
Batch2	51	50	50	50	50	50	50	50
Batch3	48	48	48	48	48	48	44	44
Batch4	52	51	51	51	52	51	50	49
Batch5	48	47	47	47	47	48	48	49
Batch6	52	47	47	48	47	46	45	45

Batch7	58	57	57	57	56	56	55	55
Batch8	52	52	52	52	55	55	55	54
Batch9	51	51	50	50	50	50	50	50

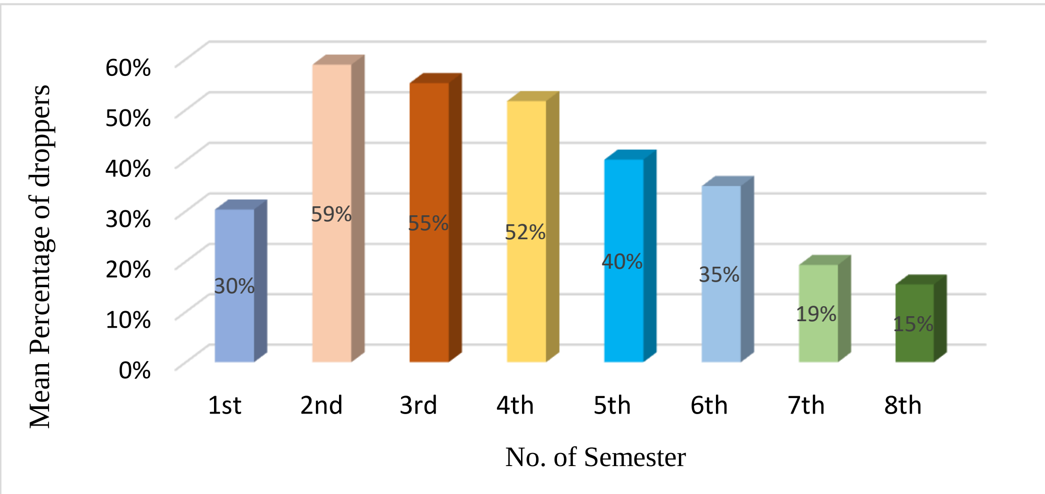
Batch-wise drop scenario

Each academic batch consists of eight semesters. Table 3 shows that the number of students participating in each semester exam also varied; this scenario is true for every batch. The reason is that the droppers from previous batches might retake some courses, or some might continue with the current batch, and current students might withdraw from the course. Table 4 shows the semester-wise percentage of droppers in each batch. In an eight-semester course duration, on average, 27% to 44% of students drop the subject in each batch. On average, 39% of students drop at least one course in every batch each semester. It is also evident that more than 50% of students fail subjects in their study period in their second, third, and fourth semesters.

Table 4 Semester-wise percentage of droppers in each batch.

Batch	Semester											
	1st	2nd	3rd	4th	5th	6th	7th	8th	Mean	Std	Max	Min
Batch1	17%	53%	39%	35%	35%	40%	21%	42%	35%	11%	53%	17%
Batch2	16%	38%	62%	54%	48%	50%	44%	38%	44%	14%	62%	16%
Batch3	29%	50%	40%	73%	44%	54%	11%	5%	38%	23%	73%	5%
Batch4	33%	69%	75%	78%	54%	47%	32%	18%	51%	22%	78%	18%
Batch5	31%	47%	72%	40%	45%	21%	10%	16%	35%	20%	72%	10%
Batch6	35%	64%	57%	29%	21%	26%	20%	7%	32%	19%	64%	7%
Batch7	34%	74%	49%	54%	50%	38%	16%	2%	40%	23%	74%	2%
Batch8	46%	71%	54%	67%	49%	27%	13%	9%	42%	23%	71%	9%
Batch9	31%	65%	50%	34%	16%	12%	6%	2%	27%	22%	65%	2%
Mean	30%	59%	55%	52%	40%	35%	19%	15%				
Std	9%	12%	13%	18%	13%	14%	12%	15%				
Max	46%	74%	75%	78%	54%	54%	44%	42%				
Min	16%	38%	39%	29%	16%	12%	6%	2%				

Figure 3 The average percentage of subject droppers in each semester



The percentage of mean dropout rate is highest in the second consecutive semester, which means in the first year, and the mean dropout rate for each semester shown in Figure 3 indicates that dropouts decrease progressively.

In figure 4, the trendlines of drops in each batch indicate that the number of new droppers (who don't drop any course in previous semesters) increases with little exception until the 4th semester and then decreases. Since there is a higher dropout rate in early semesters, why this occurs and what courses are offered in these semesters need more analysis.

Figure 4 Trendline of drops in each batch over the semester

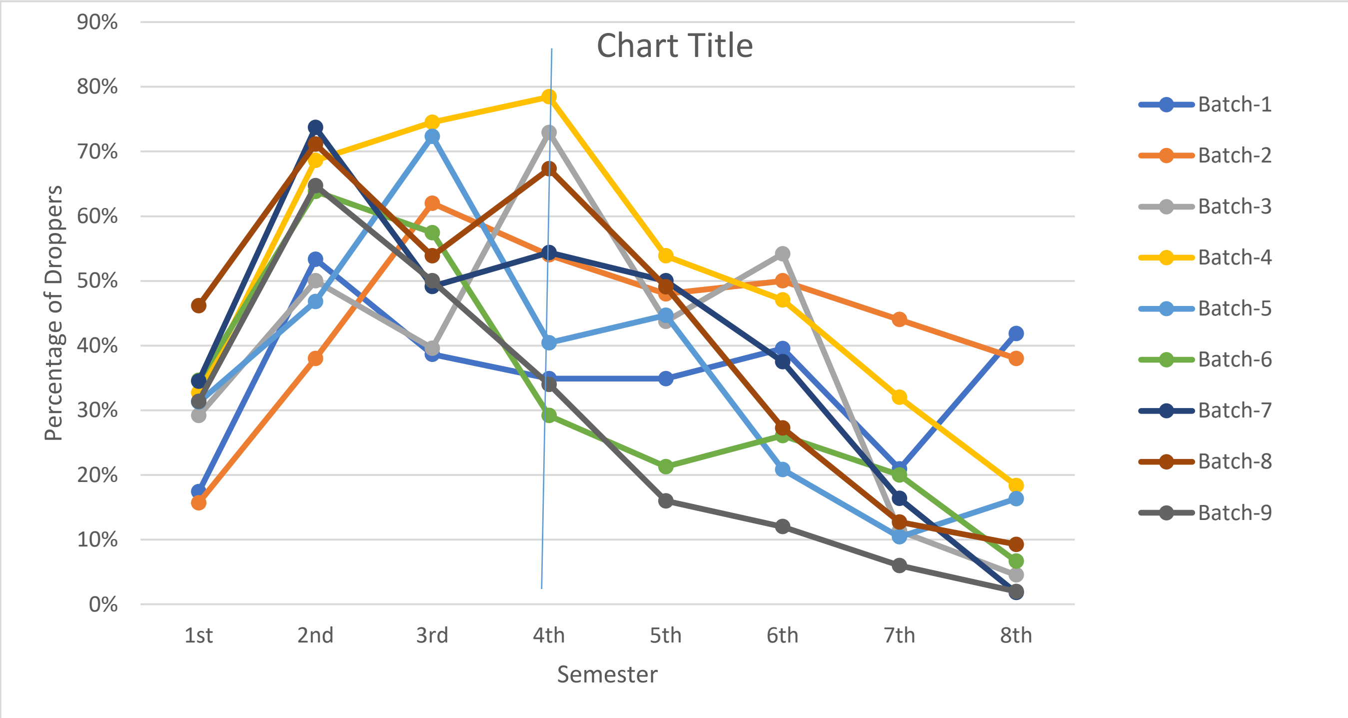
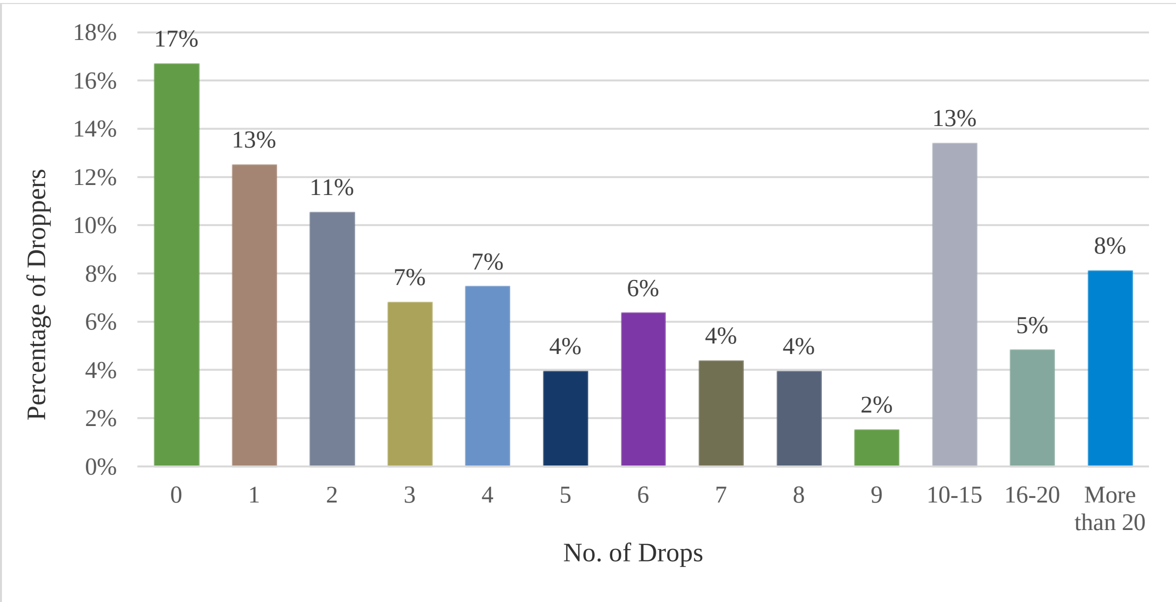


Figure 5 Percentage of droppers respective to No. of drops.



Number of Students versus Number of Drops

From Figure 5, it is clear that only 17% of students have no drops. 13% of students have dropped out once. On the other hand, 13% of students dropped 10-15 times, and 8% dropped more than 20 times.

Withdrawal concerning course category

Even though two types of courses, theory, and lab, are studied during the semester, only the theory courses are the focus of this research. These theoretical courses are classified as major, physical science, faculty elective, or social science courses. Those three categories of physical sciences, faculty electives, and social sciences are non-major courses. Analysis revealed that although the number of physical science courses is lower (only 13%) compared to other categories offered by the program, the average drop of each physical science course is highest (20%), followed by faculty elective courses (15%) and social science courses (6%) as shown in Figure 6. Again, although the percentage of major courses is highest (73%) throughout the program, the average course withdrawal is the lowest (15%) compared to other categories of courses.

Figure 6 Course-wise mean percentage of droppers in offered course during nine consecutive batches

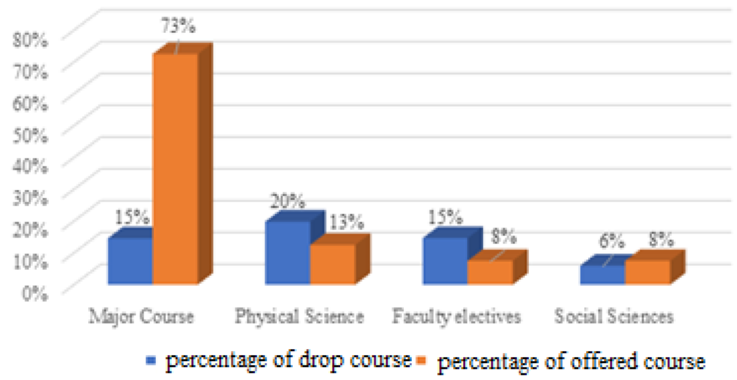


Figure 7 Percentage of course categories offered in different semesters

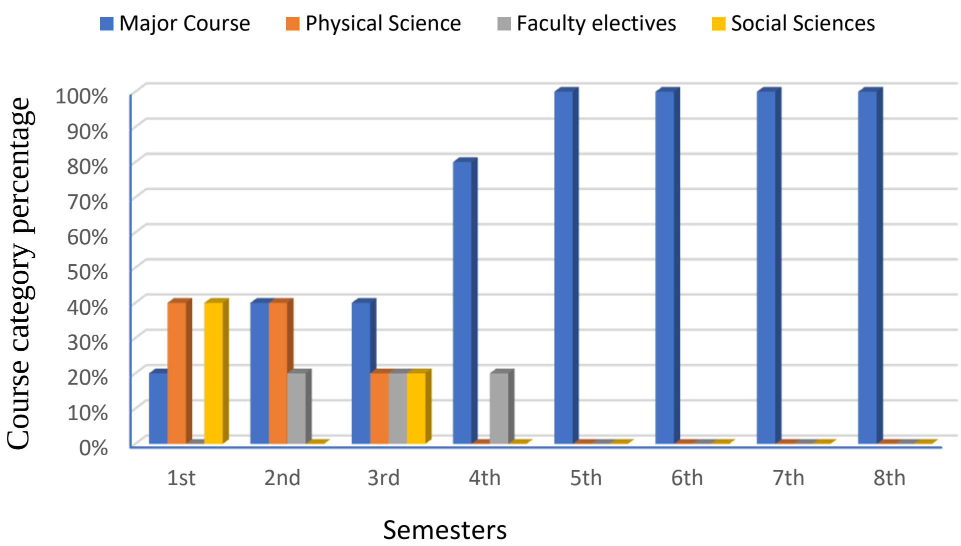


Figure 7 displays the program's course category distribution during the eight-semester study period. Figure 8 depicts how the percentage of droppers in each course category fluctuates throughout semesters. For analysis purposes, Physical Science, Faculty Elective, and Social science courses are named PS, FE, and SS, respectively. According to the findings, students dropped the physical science course nearly twice as frequently as the social science course in the first semester. Even though these two types of courses are offered at the same percentage. Further investigation revealed that they primarily dropped the core mathematics and physics courses illustrated in Figure 9. They also eliminate basic mathematics and chemistry, which are physical science course categories, during the second semester, although the percentage of available courses in major categories and physical science is the same. During the third semester, over 50% of major courses are offered, and 65% of students quit major courses, mainly thermodynamics and solid mechanics. Starting in the fourth semester, only major courses are offered, and the drop rate of students significantly decreases. In this phase, students mostly drop mechanical subjects and, in certain circumstances, applied courses.

Figure 8 Percentage of droppers in each course category across the semester

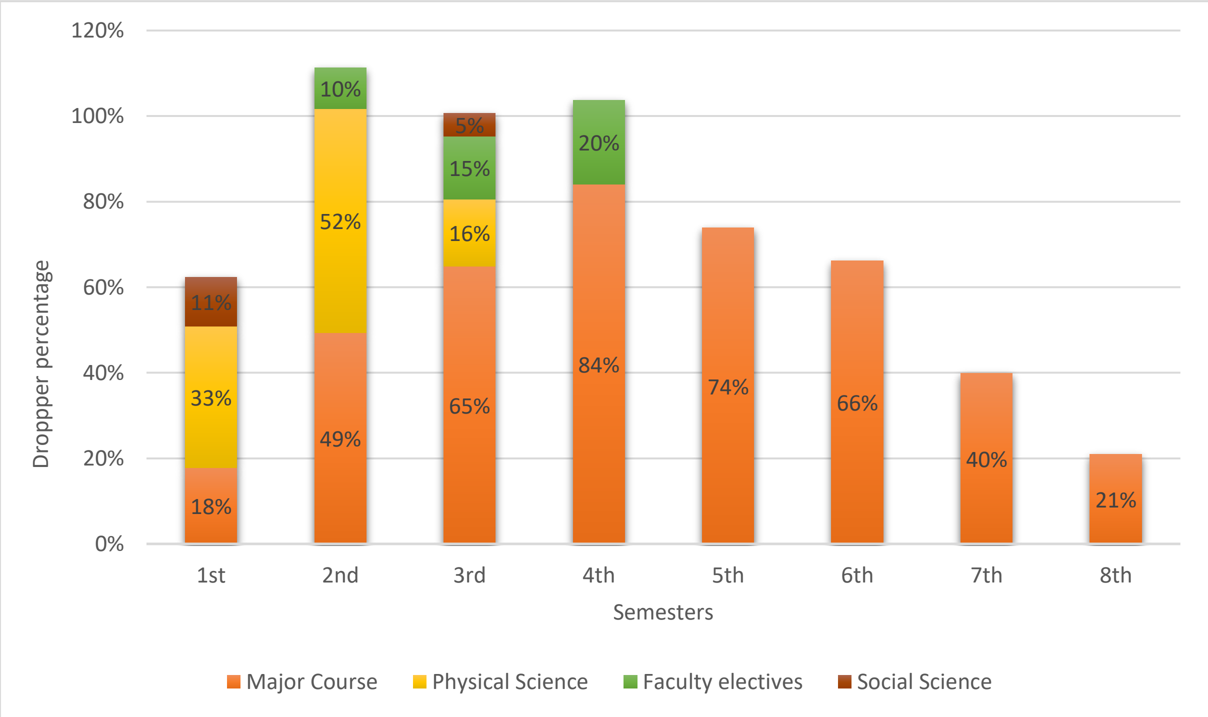
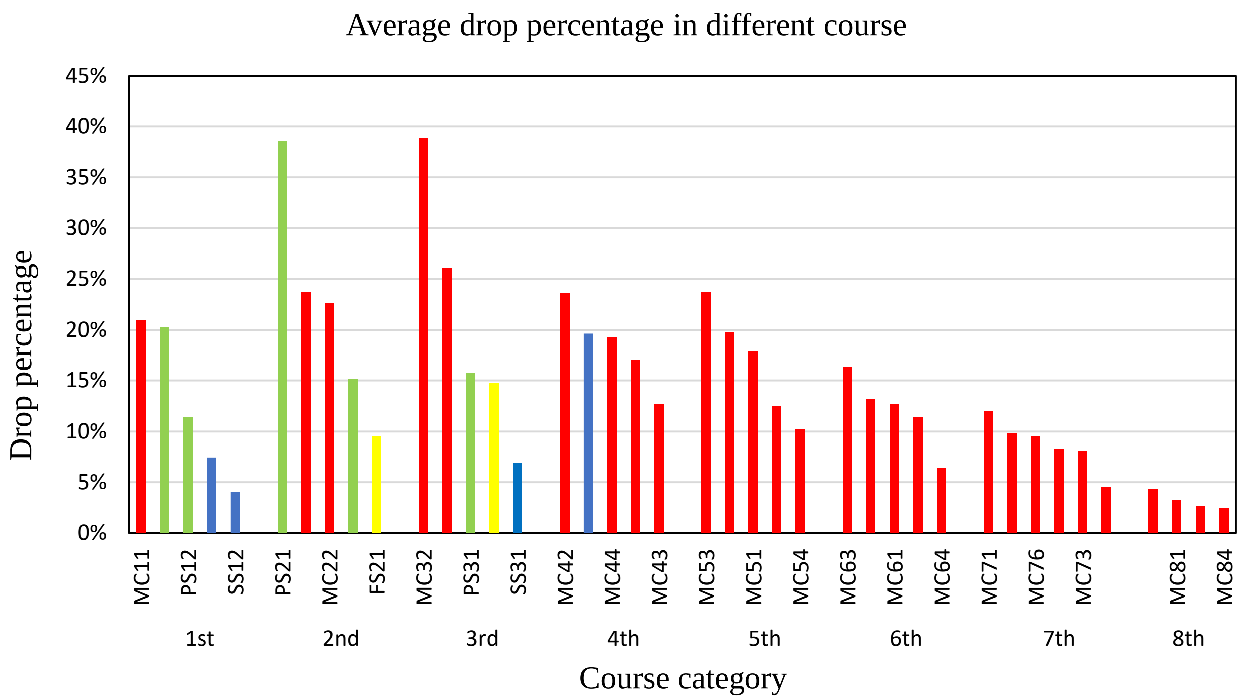
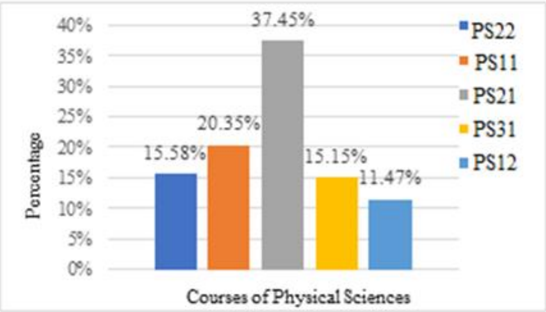


Figure 9 Top-ranked withdrew subject over eight semesters

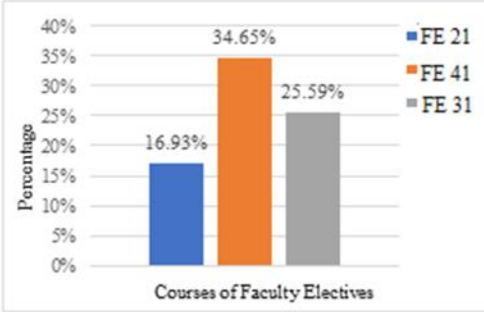


The top five physical science courses that have dropped the most are indicated in Figure 10. PS-11, PS-21, and PS-31 represent fundamental mathematics courses such as differential equations, integral calculus, etc. Overall, mathematics courses have seen the most significant drop (almost 73%), followed by chemistry (PS-22) and physics (PS-12). Similarly, the computer language course (FE-41) is the most common among faculty elective courses, followed by process engineering (FE-31) and electrical and electronics-related courses (FE-21). Sociology (SS-12) has the highest dropout rate among social science subjects. Students' perception that non-major courses are less important than major courses is one of the primary reasons for dropping these courses. In addition, students may be unable to bridge the gap between their secondary and university-level courses.

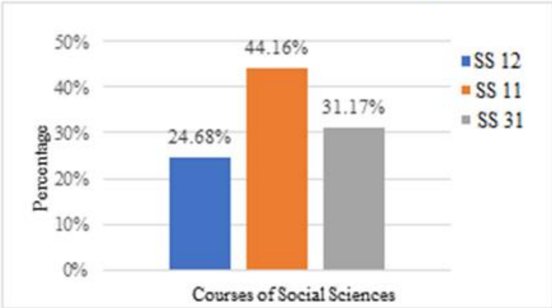
Figure 10 Percentage of non-major courses that have dropped the most
(a) Physical Science, (b) Faculty Electives, and (c) Social Sciences



(a)

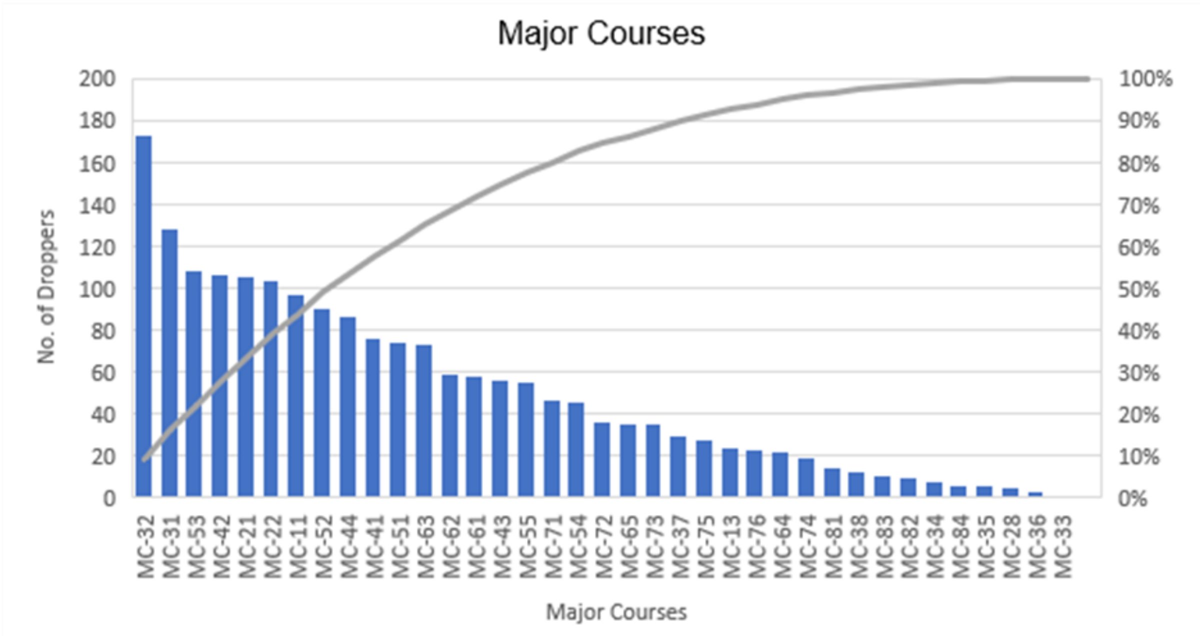


(b)



(c)

Figure 11 Number of Droppers in Major Courses



Pareto analysis determines the most often dropped courses among the major courses (MC). Figure 11 showed that over fifty percent of droppers dropped MC-32, MC-31, MC-53, MC-42, MC-21, and MC-1. These courses are available in their first, second, third, and fourth semesters. Most of the Subjects are basic mechanicals, and the reasons for the decline may be multiple. Due to a lack of quality information, an incapacity to study independently, and a tight schedule during the semester, they may be unable to adapt to the new study environment in the first year. MC-83, MC-28, MC-36, and MC-33 have the least droppers. These courses are available during the seventh, eighth, and, to some extent, the sixth semester, most of which belong under the category of applied courses. Only one course was determined to be drop-free.

Analysis of Causes of Course Withdraw

In this research, 23 causes under three primary factors, such as personal cause (PC), course consideration (CC), and institutional consideration (IC), that influence the students to dropout, are identified. Hence, a questionnaire with 23 causes under three primary factors is developed. The sample size is 319, which was calculated. The analysis is performed with 319 data sets. The questions regarding causes behind course drop were formed based on a Likert scale in the order of 5 getting the highest priority to 1 getting the lowest priority. The reliability of the questionnaire is tested with Cronbach's Alpha test; then the RII test is performed to observe the relative ranking of the variables. After that, factor analysis is done to find the root causes behind course drop and consequences. For analysis purposes, the questionnaire's personal cause (PC) is named PC1 for unsatisfactory exam preparation, PC2 for imbalance between social life and academic commitment up to PC11, and the other causes are also abbreviated, as shown in Table 8. Analysis of course drop is performed using different tools and techniques.

Reliability Test

Reliability is a measure of the stability or consistency of a prepared questionnaire. This study uses Cronbach's alpha (Cα) to test internal consistency (Jain and Angular 2017). The scale's reliability is determined by obtaining a sample size of 319. Each of the respondents was asked 26 questions. The Reliability coefficient α ranges from 0 to 1. Qualitative descriptors of Cronbach alpha (Jain and Angular 2017) are given in Table 5. Table 6 shows Cronbach's alpha (Cα) for different categories of causes.

Table 5 Qualitative descriptors of Cronbach's alpha (Cα)

Cronbach's alpha (Cα)	Internal consistency
$C\alpha \geq 0.9$	Excellent
$0.9 > C\alpha \geq 0.8$	Good
$0.8 > C\alpha \geq 0.7$	Acceptable
$0.7 > C\alpha \geq 0.6$	Questionable
$0.6 > C\alpha \geq 0.5$	Poor
$0.5 > C\alpha$	Unacceptable

Table 6 Reliability Statistics for different categories of cause group

Category	Types	Number of Items	Cronbach's alpha (Cα)
Cause group	Personal cause	11	0.731
	Course consideration	8	0.704
	Institutional consideration	17	0.567
Overall	Overall causes	23	0.854

Here, all the data show values above 0.69, which signifies the data are reliable for further study. Only institutional consideration gained a value less than 0.6.

Interrelationship between Immediate Factors

The interrelationship between immediate factors was tested using Spearman's correlation coefficient test statistics that measure the statistical relationship, or association, between two continuous variables. This coefficient assumes that there is a linear relationship between the two variables. Two variables are causally related, meaning one is independent and the other is dependent (Hasan et al., 2018). In Table 7, it is clear that some sources of causes are strongly correlated to one another.

Table 7 Correlations among immediate factors

	Unsatisfactory exam preparation	Imbalance between social life and academic commitment	Irregular in class	Encounter difficuly to study independently	Not understand the course material	negative influence of peer group	Physical and mental illness & stress	Distracted by love & affection by dearones	Excessive engarge in social media	Lack of positive motivation by peer group & others.	Financial problems	Unclear lecture delivery	Lack of feed back from teacher	lack of quality learning materials	Boring presentation by the teachers	Course content not accomplished completely & properly	Course teacher not attracted	Unable to bridge between contents and its practical application	Not interested in the course itself	Lack of expected interaction by discipline	Inappropriate institutional learning environment	Lack of institutional motivation	Gap between study pattern HSC level & University
Unsatisfactory exam preparation	1.000	.314**	.167**	0.083	0.110	0.041	-0.013	-0.051	0.105	-0.025	-0.063	.275**	.176**	.140*	.144**	0.097	.110*	0.055	-.173**	.215**	-0.018	.141*	0.063
Imbalance between social life and academic commitment		1.000	.451**	.189**	.218**	.117*	.129*	0.068	.128*	.118*	-0.014	.196**	.176**	.167**	.174**	0.071	.161**	0.094	-0.008	.147**	.116*	.217**	0.027
Irregular in class			1.000	.237**	.184**	.223**	.240**	.157**	.134*	.240**	.198**	.194**	.197**	.218**	.246**	0.106	0.105	0.082	.164**	.212**	.163**	.444**	0.101
Encounter difficuly to study independently				1.000	.319**	0.045	.315**	.265**	.397**	.202**	.231**	.133*	.329**	.277**	.209**	.234**	0.106	0.056	.127*	.185**	.213**	.128*	.173**
Not understand the course material					1.000	0.092	.299**	.228**	.250**	.247**	.248**	.208**	.339**	.250**	.289**	.269**	.131*	.224**	.145**	.153**	.322**	.186**	.265**
negative influence of peer group						1.000	.263**	.223**	0.077	.220**	.152**	0.107	.138*	.192**	.161**	.164**	.228**	0.057	.203**	0.080	.246**	.192**	.133*
Physical and mental illness & stress							1.000	.264**	.300**	.316**	.360**	.201**	.217**	.245**	.335**	.179**	.230**	0.089	.277**	.167**	.365**	.250**	.161**
Distracted by love & affection by dearones								1.000	.214**	.278**	.237**	.181**	.173**	.158**	.236**	.284**	.186**	.321**	.239**	.121*	.228**	.182**	.245**
Excessive engange in social media									1.000	.216**	.251**	.120*	.267**	.238**	.176**	.274**	.197**	.167**	.115*	.245**	.275**	.147**	.181**
Lack of positive motivation by peer group & others.										1.000	.332**	.190**	.197**	.185**	.386**	.291**	.178**	.210**	.240**	.320**	.340**	.220**	.121*
Financial problems											1.000	.142*	.326**	.171**	.190**	.258**	.156**	.193**	.368**	.228**	.301**	.191**	.291**
Unclear lecture delivery												1.000	.244**	.383**	.347**	.162**	.246**	0.081	0.052	.248**	0.077	.129*	0.023
Lack of feed back from teacher													1.000	.234**	.309**	.210**	.153**	.111*	.269**	.275**	.163**	.137*	.202**
lack of quality learning materials														1.000	.436**	.244**	.327**	0.096	0.041	.276**	.130*	.215**	0.087
Boring presentation by the teachers															1.000	.334**	.355**	.241**	.243**	.324**	.229**	.238**	0.103
Course content not accomplished completely & properly																1.000	.124*	.254**	.245**	.281**	.302**	.242**	.258**
Course teacher not attracted																	1.000	.210**	.115*	.173**	.286**	.152**	0.089
Unable to bridge between contents and its practical application																		1.000	.163**	.200**	.267**	.181**	.117*
Not interested in the course itself																			1.000	.165**	.280**	.167**	.249**
Lack of expected interaction by discipline																				1.000	.211**	.211**	.223**
Inappropriate institutional learning environment																					1.000	.285**	.389**
Lack of institutional motivation																						1.000	.168**
Gap between study pattern HSC level & University																							1.000

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Criteria Importance Rating

After data collection, the attributes in terms of their weightage as perceived by the respondents are first ranked according to the relative importance index (RII). The RII is calculated using equation 1, and the ranking of three immediate causes by category and overall ranking are given in Table 8.

The importance level of each category was identified by converting the RII value. Here, High (H);($0.8 \leq RI \leq 1$), High-Medium(H–M);($0.6 \leq RI < 0.8$), Medium(M); ($0.4 \leq RI < 0.6$), Medium–Low(M–L); ($0.2 \leq RI < 0.4$), and Low (L); ($0 \leq RI < 0.2$) (Akadiri, 2011).

$$RII = \Sigma W/(A*N) \qquad (1)$$

Where W=Weight given to each factor by the respondents; A=Highest weight; N=Total number of respondents.

As illustrated in Table 8, no lower importance (L) level status exists in any course-related, personal and institution-related factors. Hence, it is indicated that none of the questions is negligible.

Factor Analysis

Factor analysis has been performed to reduce factors into highly predictive cause determinants. The components with eigenvalues of 1.00 or higher are considered worth analyzing. The components with small eigenvalues are omitted due to having the lowest variance (Tabachnick and Fidell 1996). Using RII, the significant criteria are identified. Under a particular group, the relationship between the criteria is also identified. By factor analysis, the relative importance of the variables is identified. These are the root causes behind the course drop. To ensure whether the variables satisfy the condition for factor analysis, the KMO test and Bartlett's Test of sphericity are performed.

KMO and Bartlett's test

The sample adequacy test of all data suggested significant correlations between variables. Results showed that the p-value of Barlett's test is lower than 5%, Kaiser-Meyer Olkin's (KMO) value is higher than 5%, and Barlett's sphericity test is significant (Shkeer, 2019).

Table 8 Ranking of causes behind course drop

Immediate factors	Category	Reasons behind course drop	RII	Ranking by category	Overall ranking	Importance level
Personal cause (PC)	PC1	Unsatisfactory exam preparation	0.786	1	1	H-M
	PC2	Imbalance between social life and academic commitment	0.735	2	3	H-M
	PC3	Irregular in Class	0.623	3	7	H-M
	PC4	Encounter difficulty in studying independently	0.602	4	12	H-M
	PC5	Not Understand the course material	0.597	5	14	M
	PC6	Negative influence of peer group	0.542	6	18	M
	PC7	Physical and mental illness & stress	0.518	7	19	M
	PC8	Distracted by the love & affection of dear ones	0.496	8	20	M
	PC9	Excessive engagement in social media	0.493	9	21	M
	PC10	Lack of positive motivation by peer group and others.	0.484	10	22	M
	PC11	Financial problems	0.442	11	23	M
Course consideration (CC)	CC1	Unclear lecture delivery	0.763	1	2	H-M
	CC2	Lack of feedback from teacher	0.698	2	4	H-M
	CC3	lack of quality learning materials	0.658	3	5	H-M
	CC4	Boring presentation by the teachers	0.639	4	6	H-M
	CC5	Course content not accomplished completely & properly	0.622	5	8	H-M
	CC6	Course teachers are not attracted	0.561	6	16	M
	CC7	Unable to bridge between	0.545	7	17	M

		contents and its practical application				
	CC8	Not interested in the Course itself	0.512	8	9	M
Institutional consideration (IC)	IC1	Lack of expected interaction by discipline	0.607	1	10	H-M
	IC2	Inappropriate institutional learning environment	0.606	2	11	H-M
	IC3	Lack of institutional motivation	0.599	3	13	M
	IC4	Gap between study pattern HSC level & University	0.576	4	15	M

Table 9: KMO and Bartlett's test for immediate causes

Immediate Factors	KMO Measure of Sampling Adequacy	Bartlett's Test of Sphericity		
		Chi-Square	df	significance
Personal orientation	0.782	552.110	55	0.00
Course-related	0.779	374.535	28	0.00
Institutional related	0.639	109.966	6	0.00

In Table 9, KMO values for PC, CC, and IC are 0.782, 0.779, and 0.639, respectively. Barlett's test of sphericity is significant. These values satisfy the condition for factor analysis of the data set.

Significant Root Causes Behind Course Drop

According to the result of factor analysis, the most common root cause behind the course drop is the imbalance between social life and academic commitment; other root causes are presented in Table 10. Regarding personal causes, factors PC2, PC6, and PC4 are responsible for 51% of total variances. Among the course-related factors, the dominating root cause is CC3, almost 48% of the total variances, while IC2 is a significant root cause related to institutional factors.

Table 10 Factor loading of causes behind Course drop after varimax rotation

	Observed variables	Factor analysis value
PC2	Imbalance between social life and academic commitment	0.815
PC6	Encounter difficulty in studying independently	0.740
PC4	Negative influence of peer group	0.673
CC8	Not interested in the Course itself	0.671

CC3	lack of quality learning materials	0.652
IC2	Inappropriate institutional learning environment	0.753

Interrelationship among Root Causes

Spearman correlation has been identified to test the interrelationship between the root causes, and the results have been presented in Table 11.

Table 11 Correlation among root causes

Root cause	Imbalance between social life and academic commitment	Negative influence of peer group	Encounter difficulty in studying independently	Not interested in the Course itself	lack of quality learning materials	Inappropriate institutional learning environment
Imbalance between social --life and academic commitment	1.00	.117*	.189**	-0.01	.167**	.116*
Negative influence of peer group		1.00	0.04	.203**	.192**	.246**
Encounter difficulty in studying independently			1.00	.127*	.277**	.213**
Not interested in the Course itself				1.00	0.04	.280**
lack of quality learning materials					1.00	.130*
Inappropriate institutional learning environment						1.00

**Correlation is significant at the 0.01 level (2-tailed),

*Correlation is significant at the 0.05 level (2-tailed).

Validation of the Conceptual Model

Structural Equation Modeling (PLS-SEM 4.0) validates the conceptual model. It is advisable to have indicator loadings surpassing 0.70, demonstrating that the underlying construct accounts for over 50% of the variation in the indicators, thereby ensuring satisfactory item reliability. Nevertheless, outer loadings exceeding 0.65 are also deemed acceptable (Wong, 2013; Hair et al., 2019). In Table 12, all the indicator loadings exceed 0.7, indicating a robust connection between the indicators and their latent variables, thus affirming their appropriateness as indicators.

The Variance Inflation Factor (VIF) is employed to gauge collinearity among the indicators. Ideally, VIF values should be below five (Sarstedt et al., 2021). In Table 12, all VIF values are less than 5.

Table 12 Outer loading of the indicators.

Factors	Personal Causes	Course-related Causes	Institutional Causes	Related	No. of Drops	VIF
PC1	0.713					2.380
PC2	0.762					2.806
PC3	0.720					2.018
PC4	0.746					1.931

PC5	0.706				1.787
PC6	0.726				1.861
PC7	0.733				2.117
PC8	0.705				1.993
PC9	0.748				2.256
PC10	0.741				2.261
PC11	0.729				2.633
CC1		0.736			1.796
CC2		0.719			1.642
CC3		0.755			1.960
CC4		0.781			1.935
CC5		0.719			1.710
CC6		0.716			1.753
CC7		0.715			1.816
CC8		0.765			2.005
IC1			0.727		1.399
IC2			0.796		1.489
IC3			0.751		1.431
IC4			0.753		1.506
Drops				1.000	1.000

*PC= Personal Causes, CC = Course related Causes, IC= Institutional related Causes

Reliability and Validity

To thoroughly evaluate the structural model, it is essential to assess the reliability and validity of the latent variables. Cronbach's alpha is a commonly employed measure to gauge a scale's internal consistency and reliability. It provides a value ranging from 0 to 1, with higher values indicating stronger internal consistency among the scale items. Typically, a Cronbach's alpha of 0.7 or greater is acceptable, while values exceeding 0.8 indicate high reliability (Hair et al., 2011).

Another indicator of scale reliability is composite reliability, which is determined by the standardized loadings of the items on the latent construct. Like Cronbach's alpha, composite reliability falls within the 0 to 1 range, with higher values denoting increased reliability. Hence, Cronbach's alpha and composite reliability are two measures used to evaluate internal consistency and reliability, with specific thresholds signifying the level of reliability (Hair et al., 2019). Composite reliability values for both constructs met the required threshold point of 0.70, as noted by Hair et al. (2011).

When the Average Variance Extracted (AVE) value reaches or exceeds 0.50, it indicates that the items collectively assess the core concept and confirm their reliability (Fornell and Larcker, 1981). In Table 13, all the variables' AVE values exceed 0.5. Following the criteria established by Fornell and Larcker (1981), discriminant validity is established when the square root of the AVE for a construct surpasses its correlation with all other constructs. Table 13 presents the square root of AVE values for the constructs, all of which are higher than their correlations with other constructs. Therefore, based on this analysis, it can be concluded that discriminant validity has been established.

Table 13 Reliability and Validity analysis among the latent variables.

Latent Variable	CA	CR	AVE	Fornell-Larcker Criterion			
				1	2	3	4
1. Personal Causes	0.913	0.926	0.533	0.730			
2. Course-related Causes	0.881	0.906	0.546	0.442	0.739		
3. Institutional Related Causes	0.753	0.843	0.573	0.546	0.460	0.757	
4. No. of Drops	1.000	1.000	1.000	0.679	0.564	0.642	1.000

CA = Cronbach's Alpha, CR = Composite Reliability, AVE = Average Variance Extracted. The diagonal elements in the Fornell-Larcker criterion (bolded) are the square root of average variance extracted (AVE). Off-diagonal elements are the correlations.

Heterotrait-Monotrait (HTMT) Ratio

The HTMT (Heterotrait-Monotrait) ratio is used to evaluate discriminant validity in structural equation modeling or confirmatory factor analysis. It assesses whether a construct is distinct from other constructs in a research model, examining if the items measuring one construct correlate more strongly with each other than with items measuring other constructs. According to Kline (2023), keeping the HTMT ratio at 0.85 or lower is generally recommended. A lower HTMT ratio indicates stronger discriminant validity in this context, implying that the constructs are effectively separate. The statement suggests that all constructs in Table 14 have HTMT ratios below 0.85, demonstrating good discriminant validity, which is a favorable result supporting the distinctiveness of the measured constructs in the study.

Table 14 HTMT values for the latent variables.

Latent Variable	Personal Causes	Course-related Courses	Institutional Related Causes	Q^2
Personal Causes				0.431
Course-related Causes	0.483			0.413
Institutional Related Causes	0.647	0.569		0.291
No. of Drops	0.699	0.597	0.732	1.000

Evaluation of the Structural Model

Estimating the structural model is a pivotal step in the Structural Equation Modeling (SEM) process. This evaluation is crucial for ensuring the validity, reliability, and informativeness of the analysis results and understanding the strength and direction of relationships between constructs in the model. Several assessment criteria can be employed to evaluate the structural model in SEM, which are detailed as follows:

(i) Multicollinearity: Multicollinearity, which assesses the degree of correlation among predictor variables, is examined using measures like the Variance Inflation Factor (VIF). This helps ensure no excessive correlation between predictors, as presented in Table 16.

(ii) R^2 Values: R^2 values pertaining to dependent variables indicate the proportion of variance explained by the model. Higher R^2 values suggest a stronger predictive power. The R square values can be found in Table 15.

(iii) Cross-Validated Redundancy (Q^2) Values: Q^2 values, which measure endogenous variables' predictive relevance, are evaluated to gauge how accurately the model's predictions align with the actual data. These values are also displayed in Table 15.

(iv) Significance and Magnitude of Path Coefficients: The significance and size of path coefficients are analyzed to gain insight into the strength and relationships between the hypotheses being tested. The β value, which represents the path coefficient, is presented in Table 16.

(v) Bootstrap Confidence Intervals: Bootstrap confidence intervals for path coefficients are computed to estimate the estimated relationships' precision and reliability. These confidence interval values can be found in Table 16.

In summary, these assessment criteria collectively contribute to a comprehensive evaluation of the SEM structural model, ensuring that the analysis results are robust and meaningful for understanding the relationships between the variables in the model.

Table 15 R^2 values of the dependent variables.

	R Square	R Square Adjusted	Q^2
No. of Drops	0.609	0.606	0.592

Table 16 Hypothesis Testing Result.

Hypothesis		β	STDEV	T Statistics	P Values	VIF	Confidence Interval	
							2.50%	97.50%
H1	PC -> No. of Drops	0.402	0.043	9.283	0	1.526	0.317	0.486
H2	IC -> No. of Drops	0.311	0.038	8.104	0	1.556	0.234	0.386
H3	CC -> No. of Drops	0.243	0.039	6.261	0	1.358	0.167	0.318

*** PC = Personal Causes, IC = Institutional related Causes, CC = Course related Causes.

Top of Form

H1: Personal causes influence course drop decision.

Hypothesis 1 relates the personal causes with the number of drops. It is supported as (β=0.402, t=9.283, p=0).

H2: Institutional causes influence course drop decision.

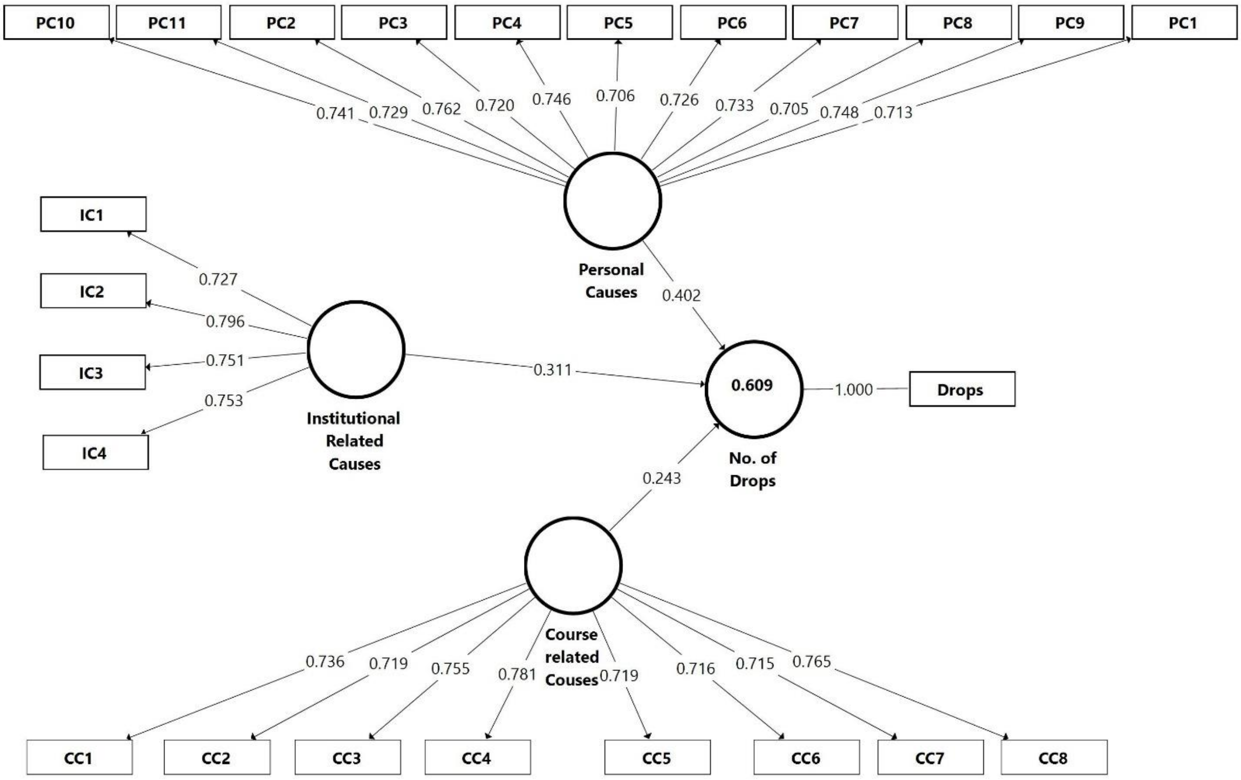
Hypothesis 2 identifies how course drop is related to institutional causes and is supported by (β=0.311, t=8.104, p=0).

H3: Course-related causes influence course drop decision.

Hypothesis 3 investigates the relevance of course-related causes with the number of drops, and the hypothesis is supported by (β=0.243, t=6.261, p=0).

The developed model summary is visually represented in Figure 12.

Figure 12 Path coefficient and T values of the developed model



Discussion

The primary objective of this study was to develop a dropout scenario among engineering students. The study found that about 83 percent of students dropped several courses in their study period, while only 17 percent were regular. It means that most students fail courses at any stage of their student life, which is a cause for concern. Batch-wise dropper percentages were calculated using Excel from the data. The percentage mean dropout rate is highest in the second consecutive semester, which means in the first year, where most courses in the syllabus are non-major categories.

According to descriptive statistics, the first-semester average dropout rate is 30%, starting from the second semester to 4th semester, which means the second-year dropout rate is more than 50%. It rapidly declined after the fourth semester, reaching 15% in the eighth semester. In the second year, a drop in non-major courses might be due to previous course drops in the first years. Hence, a student's first-year experience is strongly related to the subject drop in another semester (Rodríguez-Gómez et al. 2012). Hereafter, the biggest challenge is to predict the students' behavior to control course drop (Ramasubramanian et al., 2009).

Descriptive statistics were employed to understand the dropper trend in each semester. The trendlines of drops in each batch indicated that, from the first semester to the fourth semester, the number of droppers increases with minor exceptions; from the 4th semester to the 8th semester, the number of droppers decreases. The reason might stem from many sources; they did not find the course fascinating, and their previous study experience also impacted the current situation (Costa et al., 2018). Students must progressively acquire it, which has an impact on this tendency. Students need to study individually at the university level without private guidance. Some students have dropped the course only once; some dropped several times. For the study, it is also necessary to identify this situation. The findings clearly show that only 17% of students have no drops. 13% of students have a single drop, and 8% have more than 20 subject drops.

All Courses in the undergraduate program are classified into theory and lab-based courses. Theoretical courses are then subdivided into the major, physical science, faculty elective, and social science courses. Major subjects are those offered by the relevant department. Other departments, such as mathematics, physics, chemistry, social science, chemical engineering, computer engineering, electrical engineering, etc., provide the three different categories. The data on drops that occurred in individual courses were also collected and analyzed to obtain a complete dropout scenario.

When the mean percentage of droppers in nine batches is compared to the proportion of different courses offered, it is clear that while major courses are a higher number, 73 percent of total courses, only 15 percent of students dropped those courses. Although the percentage of physical science, faculty elective, and social science courses are 13%, 8%, and 8% of total courses, they have a more significant drop rate of 20%, 15%, and 6%, respectively.

The study explored the situation further in each semester to obtain an in-depth scenario. The percentage of droppers in each course category fluctuates throughout semesters. Students dropped the physical science course nearly twice as frequently as the social science course. They primarily dropped basic mathematics, such as differential equations and integral calculus, by 73%, followed by chemistry and physics during their first and second semester study period. Faculty elective courses are mainly offered in the third and fourth semesters, and students mostly drop the computer language course followed by process engineering and electrical and electronics. Sociology has the highest dropout rate among social science subjects. Students' perception that non-major courses are less important than major courses is one of the primary reasons for dropping these courses. In addition, students may be unable to bridge the gap between their secondary and university-level courses. The reason could be the fear of mathematics-related courses. Also, the learning environment significantly affects that situation.

Pareto analysis determines the most often dropped courses from the major courses (MC). More than half of droppers fall into the basic mechanical subjects available in the first, second, third, and fourth semesters. Due to a lack of basic information, inability to study alone, the semester system's strict time constraints, and other factors, they may find adjusting to the new study environment during the first year challenging. The drop scenario identifies the gap in knowledge construction’s steps. Acceleration path program is needed to reduce drop at the first-year level. Mentoring at the fresher's level is required. Also, mathematical modeling and monitoring need to be done carefully.

After developing the drop scenario, the study focused on identifying the causes behind the dropout from student perception. From the literature review and questionnaire-based survey, 23 causes are identified. The study examines the internal consistency and structure of the cause questionnaire. The items of the questionnaire were found to be consistent. The causes are divided into three categories: personal cause (PC), course consideration (CC), and institutional consideration (IC). The results showed that some have a close association with other elements. For example, unclear lecture delivery is closely related to the lack of learning materials; similarly, boring presentations by teachers are associated with the lack of feedback from the teacher. A correlation among these factors was identified using Spearman's correlation coefficient test statistics.

The relative importance index ranks the causes behind the course dropout based on their weightage. Among the personal reasons (PC), unsatisfactory exam preparation (PC1), imbalance between social life and academic commitment (PC2), irregular in class (PC3), and encounter difficulty in studying independently (PC4) have a higher RII index of 0.786, 0.735, 0.625 and 0.602 respectively and are categorized as high-medium in importance level.

Among the causes under course considerations are unclear lecture delivery (CC1), lack of feedback from teachers (CC2), lack of quality learning materials (CC3), boring presentation by the teacher (CC4), and course content not accomplished completely and properly (CC5) are in high-medium importance level. Among the causes under institutional consideration, lack of expected interaction by discipline (IC1) and inappropriate institutional learning environment (IC2) is at a high-medium importance level.

Factor analysis is performed to identify the most significant root causes. Among the 23 factors, six factors are found to be more significant. Among the 11 personal reasons, the imbalance between social life and academic commitment, the negative influence of peer groups, and the difficulty of studying independently have higher factor loading values of 0.815, 0.673, and 0.740, respectively, 51% of total variances of a personal cause. Among the eight course consideration-related causes, only two are more significant: not interest in the course itself and lack of quality learning materials. Only one institutional reason is found to be most important: inappropriate institutional learning.

The conceptual framework (Figure 1) links the different causes, such as personal, institutional, and course-related. The issue of course drop is increasing at an alarming rate in Bangladesh's public universities. The course drop gradually causes the lingering of the academic tenure of the students and, in some cases, becomes the reason for dropping out from their academic careers. The current study highlights the linkage between subject drop and its relevant causes and provides some generalized guidelines to avoid the situation. Three hypotheses have been developed based on the three reasons for subject drops. The hypotheses have been validated through SEM analysis with PLS SEM 4.0. All the developed hypotheses have been tested, and the results shown in Tables 12 to 15 validate the conceptual framework and the hypotheses.

Preventive Measures

Course drop is a multi-attribute phenomenon since the reason behind the course drop consists of interaction among various personal and contextual factors. Based on the result and analysis, some suggestions are recommended to reduce course drop.

- The required preventive measures should be taken from the first semester to the fourth semester to decrease the number of drops and number of droppers.
- Students need to pay attention to their non-major courses as well. These courses are responsible for the highest number of drop occurrences.
- Students should give more importance to attending classes and more effort to attain better marks on term tests. Hence, it is necessary to monitor students' activity regularly.
- Although university authorities already appointed academic advisors, attention should also be given to monitoring their residential environment.
- Supplementary exams should be included so the students would not have to wait a year to pass a course they previously failed.
- No student should be motivated toward course drop by the influence of other droppers.

- Although the university authority already started the dope test before admission. It would be more effective if the test is done before confirming registration in each semester.
- Regular counseling and effective parental control are important to reduce personal problems.
- The academic calendar should be strictly maintained. Classes need to be taken according to the given time in the routine and the required number of classes at the right time.

Conclusions

The finding revealed that a high percentage of students, 83%, have dropped at least one point in their study period. Although the drop scenario is not the same in all the batches, starting from the first semester to the fourth semester, the number of course drops increases significantly; after the fourth semester, the number of drops decreases linearly. Most students drop subjects (above 50%) in their early period, which means in the first year, where most of the courses are non-major categories, mainly in physical science, in the second year, the student drops basic mechanical courses offered by the relevant department. The findings clearly show that only 17% of students have no drops. Thirteen percent of students have a single drop, and 8% have more than 20 subject drops. The course drop is due to personal, course-related, and institutional considerations. During the first year of the study period in the undergraduate engineering program, students find it challenging to cope with the new environment, medium of instruction, educational system, etc.; for that reason, course dropout occurs mainly at that time. The analysis finds six root causes out of 23 causes. Three personal causes such as an imbalance between social life and academic commitment, encounter difficulty in studying independently, the negative influence of peer groups, two course-related factors such as not being interested in the course itself, lack of quality learning materials, and one institutional consideration such as Inappropriate institutional learning environment are the root cause behind the course drop. The correlation among the root causes is found to be statistically significant. The developed framework was tested and validated based on the results and extensive literature review. All the developed hypotheses are tested and found to be statistically significant. Finally, some suggestions are provided which might reduce the number of course drops. In a further study, an effective teaching-learning approach needs to be explored and adopted to reduce the consequences of drop, which might be psychological, academic, and financial.

Acknowledgment

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