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Is equal weightage in all summative assessments fair to undergraduate student?

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Abstract

Learning is often quoted as a lifelong process. In other words, life is about learning. As prominent institutions, universities are concerned with valued and measurable learning among undergraduate students so that their mastery level of a particular content knowledge can be quantitatively gauged. Of many types of assessments, summative assessment plays a greater role in majority of engineering courses due to nature of the content knowledge. This paper mathematically investigates the fairness issue of equal weightage for all summative assessments i.e., assignments, mid-term test and end-term examination. A multiple objective optimization on the basis of ratio analysis (MOORA) is utilized to assign equal weight for the aforementioned assessments. It was found that the number of students failing the selected engineering course increases by about five times using the MOORA method. The finding clearly reveals the advantages of the former method (unequal weights) as compared to MOORA method in terms of catering students with different learning styles and speed of knowledge acquisition.

Keywords: assessment; summative; formative; weightage; grade

1. Introduction

Historically, universities have been established as institutions with the sole aim of creating and dispersing knowledge. However, this is no longer true in the present era of Industrial Revolution 4.0 where universities need to equip future workforce with necessary knowledge and skills pertaining to creativity, life-long learning problem solving and transferable skills, to name but a few (Pithers & Soden, 2000). In line with this, students are expected to understand content knowledge, developed subject-specific and general skills as outlined in the curriculum (Klegeris et al., 2017). For this reason, universities are concerned with valued learning which can be measured through a number of assessments.

Assessment is usually designed to measure progress of students' learning and the corresponding achievement. It could provide lecturers with extremely valuable data concerning knowledge and skill mastery. Based on the gathered data, lecturers could re-evaluate appropriate instructional approaches against diversity of learning styles. A balanced assessment system requires both summative and formative assessments (Dolin et al., 2018). In particular, summative assessments are given periodically to determine attainment of content knowledge among students. The primary goal of the assessment is to evaluate student learning at the end of learning units by comparing it against some standard or benchmark. One clear benefit of summative assessment is it helps to evaluate the effectiveness of programs and alignment of curriculum (Iannone & Simpson, 2017). Methods of summative assessment are not limited to mid-term test and semester examination but may include portfolio, project and mini-project (Dixson & Worrell, 2016; Harlen & James, 1997).

The central argument of this paper is that an unequal weightage is usually employed for a variety of summative assessments through a pre-determined percentage breakdown. This has been practiced for years in the universities (Wormeli, 2006). A question arises if this practice should be replaced with an equal weightage across all methods of summative assessments in order to provide fair opportunities for students with learning difficulties.

2. Methodology

In order to address this argument, the following characteristics of learners (**Table 1**) and methods of summative assessments (**Table 2**) are considered. The assessment consists of Assignments, Mid-term Test and End-term Examination having unequal weightage of:

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Assignments : Mid-term Test : End-term Examination = 30% : 20% : 50% (**1**)

Table 3 shows distribution of the marks for the aforementioned assessments for the entire class of 81 students. It should be noted that the passing mark for this course is 50%. Based on the criteria of unequal weightage, nine students did not pass the course (see **Table 3**). In the following section, a multiple-objective optimization on the basis of ratio analysis (MOORA) will be employed to assess the performance of the students' grade based on equal weightage as follows:

Assignments : Mid-term Test : End-term Examination = 33.3% : 33.3% : 33.3% (**2**)

Table 1: Nature of the course and characteristics of the learners

Attribute	Details
Name of Degree:	Bachelor of Mechanical Engineering
Name of Course	KNJ3163 Instrumentation and Control
Requisite:	KNJ1053 Fluid Mechanics 1
No. of Students:	81
Duration of Course	14 weeks
Frequency of Class Meeting:	Monday: 4.00 pm – 6.00 pm Thursday: 10.00am – 12.00 pm
Class Duration	2 hours
Year of Study:	Semester 2, Year 3

Table 2: Methods of summative assessments

Summative Assessment	Mark (%)	Date of Assessment
Assignment	30	Week 4, 10, 12
Mid-term Test	20	Week 8
End-term Examination	50	Week 15

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Table 3: Distribution of marks for different methods of summative assessments for the entire class (81 students in total)

Student ID	Assignment (30%)	Test (20%)	Exam (50%)
1	18.7	12.0	28.5
2	22.5	18.0	28.3
3	23.1	8.0	38.0
4	23.2	17.0	34.5
5	19.1	16.0	23.0
6	18.7	18.0	33.0
7	25.2	18.0	39.5
8	20.8	14.0	42.3
9	22.7	14.0	41.5
10	20.7	4.0	22.8
11	20.1	6.0	29.3
12	22.3	10.0	34.5
13	21.9	11.0	31.3
14	21.8	18.0	39.3
15	19.8	16.0	34.5
16	22.5	20.0	37.8
17	22.9	16.0	37.5
18	22.9	13.0	41.0
19	21.5	7.0	26.0
20	21.5	12.0	24.5
21	21.5	16.0	26.5
22	22.3	12.0	29.0
23	24.9	18.0	42.0
24	22.6	8.0	28.5
25	19.2	18.0	24.8
26	24.2	16.0	28.8
27	23.5	15.0	37.0
28	20.3	5.0	24.8
29	22.2	16.0	31.3
30	24.0	18.0	27.5
31	4.3	2.0	31.0
32	21.3	14.0	29.0
33	21.4	13.0	40.3
34	23.1	13.0	30.5
35	20.9	3.0	18.0
36	22.3	4.0	20.0
37	23.5	20.0	43.3
38	22.5	2.0	23.5
39	24.0	13.0	41.5
40	24.0	13.0	31.3
41	23.7	16.0	43.0

Student ID	Assignment (30%)	Test (20%)	Exam (50%)
42	20.3	9.0	43.0
43	20.1	6.0	20.8
44	19.7	18.0	30.3
45	22.3	10.0	32.8
46	20.1	6.0	38.0
47	21.1	16.0	34.8
48	19.9	15.0	29.3
49	22.2	14.0	42.0
50	23.1	17.0	31.3
51	19.3	8.0	22.5
52	18.7	7.0	29.0
53	20.1	14.0	32.3
54	19.0	14.0	37.8
55	20.3	5.0	34.5
56	22.4	13.0	27.5
57	20.1	9.0	34.0
58	20.1	12.0	37.5
59	22.4	14.0	34.5
60	19.5	3.0	18.8
61	20.7	8.0	32.0
62	25.2	17.0	31.8
63	19.3	15.0	32.5
64	22.1	14.0	35.0
65	19.7	1.0	36.5
66	20.7	17.0	38.5
67	21.7	11.0	36.0
68	19.1	16.0	35.8
69	20.5	11.0	33.0
70	20.5	17.0	42.0
71	23.5	10.0	37.3
72	22.9	13.0	37.8
73	22.4	18.0	33.5
74	20.3	12.0	26.3
75	20.8	14.0	32.0
76	24.0	11.0	37.0
77	19.2	7.0	26.0
78	22.5	11.0	41.0
79	22.9	20.0	44.5
80	24.3	18.0	35.3
81	17.5	8.0	24.5

With the aims to maximize grade performance, MOORA is employed here to evaluate the best appropriate configuration (Tamrin, Nukman, et al., 2015; Tamrin, Sheikh, et al., 2018; Tamrin & Zahrim, 2017). MOORA approach is more straightforward as compared to adaptive neuro-fuzzy inference system (Tamrin, Zakariyah, et al., 2018). The procedure is discussed in the following steps:

As the name implies, multi-objective optimization procedure performs simultaneous optimization of all selected attributes in a given set of constrains (Tamrin, Nukman, Choudhury, et al., 2014; Tamrin, Nukman, Sheikh, et al., 2014; Tamrin, Zakariyah, et al., 2015). First, a decision matrix is constructed (Equation (3)). It consists of the measured performances of different variables for various objectives. Each values of the measured performance x_{mn} are noted for all alternatives/variables with attributes/objectives.

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & \dots & \dots & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & \dots & \dots & \dots & x_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & \dots & \dots & \dots & x_{mn} \end{bmatrix} \quad \textbf{(3)}$$

where *m* represents the total number of alternatives, while *n* represents the total number of attributes. Following this, a ratio is computed of all the performance of alternatives for an attribute using Equation (4).

$$\overset{a}{x}_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (j = 1,2,\dots,n) \quad \textbf{(4)}$$

where the normalized performance parameter x_{ij} represents i^{th} alternative on j^{th} attribute ranging from [0, 1]. At this juncture, the decision matrix is effectively normalized and this makes all attributes under consideration dimensionless and comparable. In order to optimize the configuration, these parameters are either added for maximum beneficial attributes or subtracted for minimum non-beneficial attributes, as shown in Equation (5).

$$\bar{y}_i = \sum_{j=1}^{g} w_j \cdot \overset{a}{x}_{ij} - \sum_{j=g+1}^{n} w_j \cdot \overset{a}{x}_{ij} \quad (j = 1,2,\dots,n) \quad \textbf{(5)}$$

For maximization *g* is the total number of attributes, while for minimization the number of attributions is presented by ($n-g$). Normalized value of $\bar{y}_i$ represents the assessment value for i^{th} substitute compared to all attributes. The value of $\bar{y}_i$ can be positive (maxima-beneficial attributes) or negative value (minima-negative attribute), while the ordinal ranking indicates the final preferences.

3. Results and discussion

In this study, three parameters (assignment, mid-term test and end-term examination) were measured which are responsible for the actual grade achievement, as earlier shown in **Table 3**. To simplify matters due to unequal allocation of percentages for different types of summative assessment, we resort to MOORA in determining the optimized grade, as described in the previous section. All MOORA calculations can be conveniently performed in either Microsoft Excel or MATLAB software. **Table 4** shows the results after squaring the responses of each attribute, x_{ij}^2. By using Equation (4), the normalized value of the response, $\overset{a}{x}_{ij}$ is calculated and the assessment value, $\bar{y}$ for each mode of assessment is determined based on Equation (5). The decision-making matrix results are shown in **Table 5**.

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Table 4: Results after squaring the response value for each attribute.

Student ID	Response-squared, x_{ij}^2		
	Assignment (30%)	Test (20%)	Exam (50%)
1	348.57	144.00	812.25
2	504.90	324.00	798.06
3	532.22	64.00	1444.00
4	538.24	289.00	1190.25
5	365.96	256.00	529.00
6	348.57	324.00	1089.00
7	635.04	324.00	1560.25
8	432.64	196.00	1785.06
9	516.65	196.00	1722.25
10	427.25	16.00	517.56
11	405.22	36.00	855.56
12	495.95	100.00	1190.25
13	478.30	121.00	976.56
14	475.24	324.00	1540.56
15	392.04	256.00	1190.25
16	507.60	400.00	1425.06
17	523.04	256.00	1406.25
18	523.04	169.00	1681.00
19	460.96	49.00	676.00
20	463.54	144.00	600.25
21	463.54	256.00	702.25
22	495.95	144.00	841.00
23	618.52	324.00	1764.00
24	510.76	64.00	812.25
25	368.64	324.00	612.56
26	585.64	256.00	826.56
27	553.66	225.00	1369.00
28	413.31	25.00	612.56
29	492.84	256.00	976.56
30	576.00	324.00	756.25
31	18.75	4.00	961.00
32	454.97	196.00	841.00
33	457.96	169.00	1620.06
34	535.00	169.00	930.25
35	438.06	9.00	324.00
36	495.95	16.00	400.00
37	553.66	400.00	1870.56
38	507.60	4.00	552.25
39	576.00	169.00	1722.25
40	576.00	169.00	976.56
41	560.27	256.00	1849.00
42	413.31	81.00	1849.00
43	405.22	36.00	430.56
44	386.91	324.00	915.06
45	495.95	100.00	1072.56
46	405.22	36.00	1444.00
47	443.94	256.00	1207.56
48	394.82	225.00	855.56
49	492.84	196.00	1764.00
50	532.22	289.00	976.56
51	371.33	64.00	506.25
52	348.57	49.00	841.00
53	405.22	196.00	1040.06
54	361.00	196.00	1425.06
55	413.31	25.00	1190.25
56	501.76	169.00	756.25
57	405.22	81.00	1156.00
58	405.22	144.00	1406.25
59	501.76	196.00	1190.25
60	381.42	9.00	351.56
61	427.25	64.00	1024.00
62	635.04	289.00	1008.06
63	371.33	225.00	1056.25
64	487.08	196.00	1225.00
65	386.91	1.00	1332.25
66	427.25	289.00	1482.25
67	469.59	121.00	1296.00
68	365.96	256.00	1278.06
69	419.02	121.00	1089.00
70	419.02	289.00	1764.00
71	553.66	100.00	1387.56
72	523.04	169.00	1425.06
73	501.76	324.00	1122.25
74	413.31	144.00	689.06
75	432.64	196.00	1024.00
76	576.00	121.00	1369.00
77	368.64	49.00	676.00
78	507.60	121.00	1681.00
79	523.04	400.00	1980.25
80	591.95	324.00	1242.56
81	305.20	64.00	600.25
$\sum_{j=1}^{6} x_{ij}^2$	37398.57	14282.00	90439.06
$\sqrt{\sum_{j=1}^{6} x_{ij}^2}$	193.39	119.51	300.73

Table 5: Normalized decision-making matrix and results of multi-objective optimization on the basis of ratio analysis (MOORA)

Student	Normalization			Scaled-$\bar{y}$		Student	Normalization			Scaled-$\bar{y}$
	Assignment (33.3%)	Test (33.3%)	Exam (33.3%)				Assignment (33.3%)	Test (33.3%)	Exam (33.3%)	
1	1.80	1.21	2.70	35.00		42	2.14	0.68	6.15	54.96
2	2.61	2.71	2.65	48.90		43	2.10	0.30	1.43	23.47
3	2.75	0.54	4.80	49.60		44	2.00	2.71	3.04	47.55
4	2.78	2.42	3.96	56.16		45	2.56	0.84	3.57	42.72
5	1.89	2.14	1.76	35.52		46	2.10	0.30	4.80	44.14
6	1.80	2.71	3.62	49.88		47	2.30	2.14	4.02	51.83
7	3.28	2.71	5.19	68.57		48	2.04	1.88	2.85	41.51
8	2.24	1.64	5.94	60.17		49	2.55	1.64	5.87	61.65
9	2.67	1.64	5.73	61.55		50	2.75	2.42	3.25	51.61
10	2.21	0.13	1.72	24.92		51	1.92	0.54	1.68	25.38
11	2.10	0.30	2.85	32.14		52	1.80	0.41	2.80	30.71
12	2.56	0.84	3.96	45.12		53	2.10	1.64	3.46	44.11
13	2.47	1.01	3.25	41.28		54	1.87	1.64	4.74	50.56
14	2.46	2.71	5.12	63.10		55	2.14	0.21	3.96	38.65
15	2.03	2.14	3.96	49.83		56	2.59	1.41	2.51	40.00
16	2.62	3.35	4.74	65.67		57	2.10	0.68	3.84	40.57
17	2.70	2.14	4.68	58.39		58	2.10	1.21	4.68	48.91
18	2.70	1.41	5.59	59.53		59	2.59	1.64	3.96	50.23
19	2.38	0.41	2.25	30.91		60	1.97	0.08	1.17	19.72
20	2.40	1.21	2.00	34.32		61	2.21	0.54	3.41	37.71
21	2.40	2.14	2.34	42.15		62	3.28	2.42	3.35	55.51
22	2.56	1.21	2.80	40.26		63	1.92	1.88	3.51	44.85
23	3.20	2.71	5.87	72.20		64	2.52	1.64	4.07	50.48
24	2.64	0.54	2.70	36.04		65	2.00	0.01	4.43	39.48
25	1.91	2.71	2.04	40.80		66	2.21	2.42	4.93	58.60
26	3.03	2.14	2.75	48.55		67	2.43	1.01	4.31	47.52
27	2.86	1.88	4.55	57.01		68	1.89	2.14	4.25	50.80
28	2.14	0.21	2.04	26.88		69	2.17	1.01	3.62	41.70
29	2.55	2.14	3.25	48.67		70	2.17	2.42	5.87	64.08
30	2.98	2.71	2.51	50.30		71	2.86	0.84	4.61	50.98
31	0.10	0.03	3.20	20.39		72	2.70	1.41	4.74	54.31
32	2.35	1.64	2.80	41.63		73	2.59	2.71	3.73	55.41
33	2.37	1.41	5.39	56.22		74	2.14	1.21	2.29	34.54
34	2.77	1.41	3.09	44.60		75	2.24	1.64	3.41	44.65
35	2.27	0.08	1.08	20.96		76	2.98	1.01	4.55	52.38
36	2.56	0.13	1.33	24.70		77	1.91	0.41	2.25	27.98
37	2.86	3.35	6.22	76.22		78	2.62	1.01	5.59	56.58
38	2.62	0.03	1.84	27.56		79	2.70	3.35	6.59	77.48
39	2.98	1.41	5.73	62.05		80	3.06	2.71	4.13	60.73
40	2.98	1.41	3.25	46.84		81	1.58	0.54	2.00	25.20
41	2.90	2.14	6.15	68.60						

Figure 1 shows a correlation graph between two different methods used for summative assessments grading. It shows that the MOORA method is well correlated with the existing method in terms of marks distribution with R-squared value of 98.99%. On the other hand, **Figure 2** compares the marks achieved for individual students based on those two methods. It is clear that both methods exhibit similar trends. However, it is found that the number of students fail the course increases from 9 to 49 using MOORA method. Hence, this finding answers the central argument of this paper that the equal weightage in all summative assessments is unfair to undergraduate students. One of the reasons that the former method has low number of students fail the course is that it allows students who did not do well in assignment and mid-term test the opportunities to correct their mistake and do necessary improvements for end-term examination. Since

students have different learning styles (De Bello, 1990), the former method seems accommodative for slow learners (Harlen, 2005).

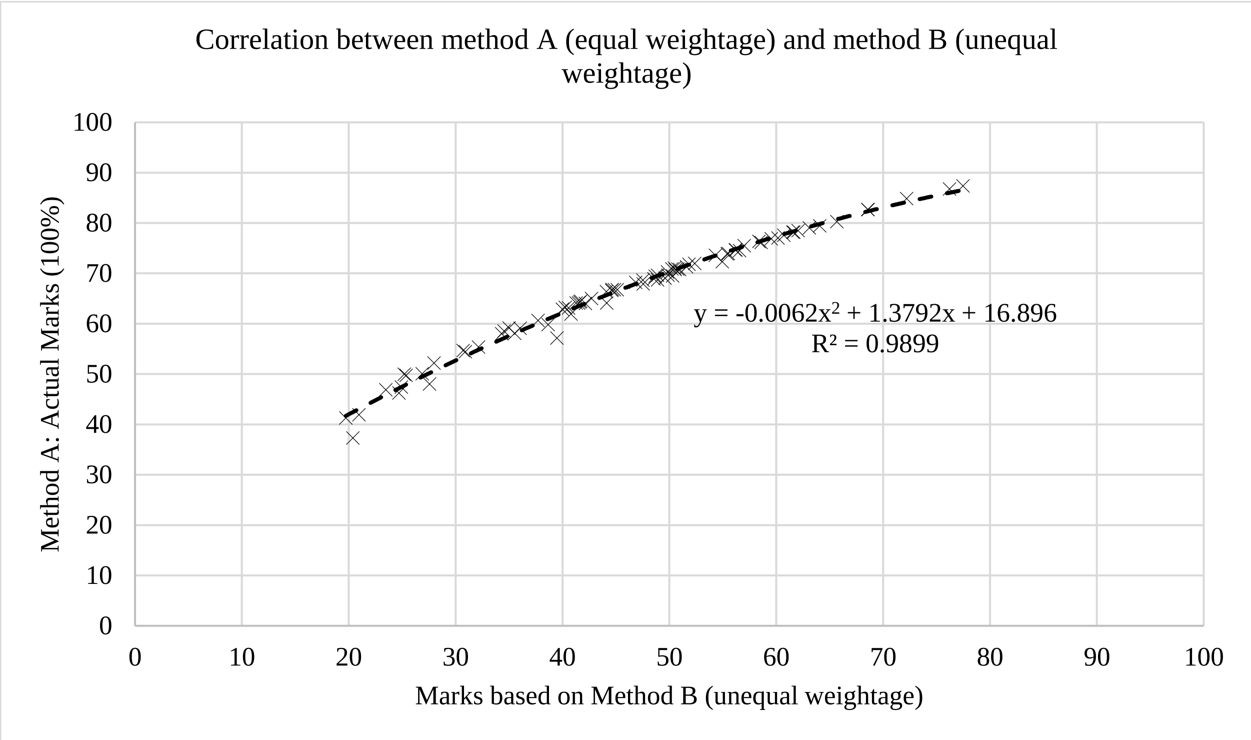

Figure 1: Correlation of marks between equal and unequal weightage distributions.

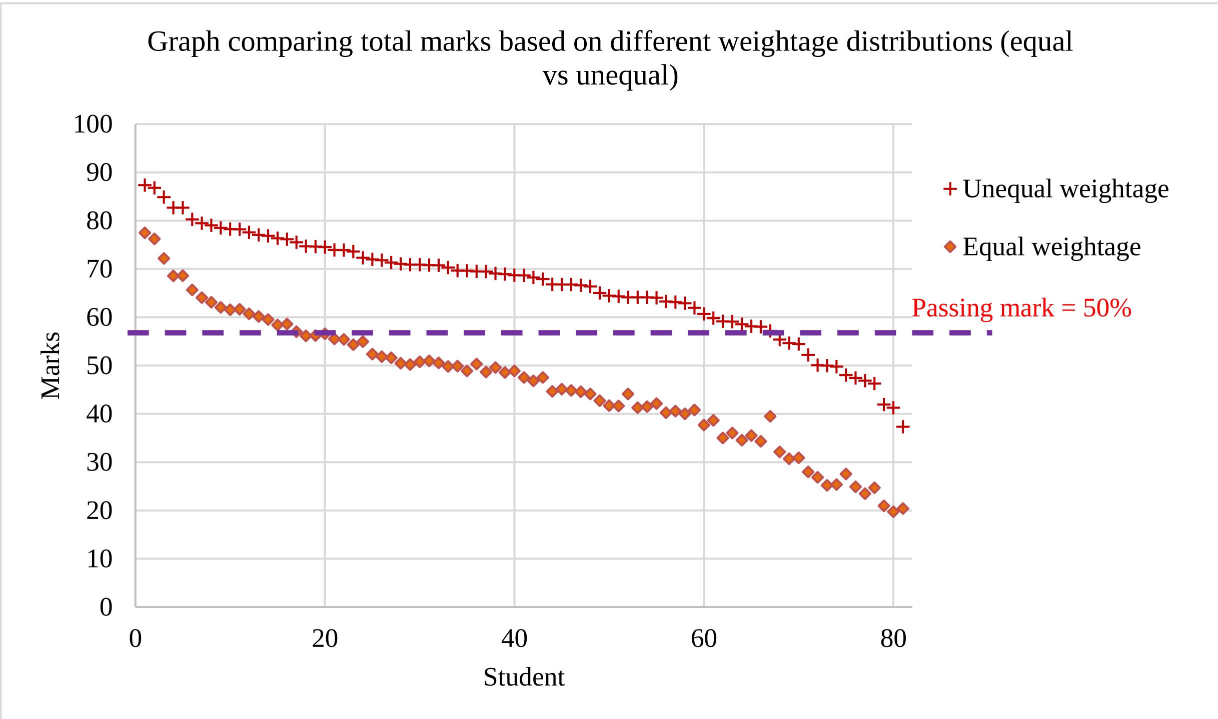

Figure 2: Graphs comparing individual student marks based on two different methods (equal and unequal weightage distributions).

4. Conclusions

Comprehensive assessment for determining mastery level of student in particular content knowledge requires both formative and summative. In majority of engineering courses, summative assessment plays more significant roles than that of summative assessment due to nature of the content knowledge. This paper mathematically investigates the fairness issue of equal weightage for all summative assessments i.e., assignments, mid-term test and end-term examination. A multiple objective optimization on the basis of ratio analysis (MOORA) was employed to assign equal weight for the aforementioned assessment. It was found that this results in the number of students failing the course increases from 9 to 49. The finding clearly shows that equal weightage for all summative assessment is unfair for students having different learning styles and pace of knowledge synthesis.

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