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Evaluating Online Learning in India: Insights from Students

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Abstract: As technology has advanced, the educational system has undergone numerous modifications. The benefits of online teaching and learning include increased accessibility, reduced costs, and the opportunity to learn at any time and from any location. However, a few drawbacks of this approach include a decline in student involvement, a lack of face-to-face interaction with classmates and teachers, and technical difficulties. Improving the online teaching and learning mechanism from the student's perspective is crucial to enhance its use. In this study, we closely examine the challenges that students encounter when studying online and rank the perspectives with an aim to improve their participation and engagement. This study is based on a dataset gathered online during COVID-19 to assess the problems and perspectives of students and teachers involved in online teaching learning. Purposive sampling was used to collect data from 683 totally completed questionnaires for the study. We use statistical and decision-making approaches, including RIDIT, TOPSIS, and RII, to examine the data from multiple viewpoints related to online learning, including student motivation, platform usability, instructional quality, and accessibility. The study evaluates these components based on how they affect student participation: Academic and emotional. The ensemble majority voting method combines the findings obtained from the tools used. Additionally, the outcome of Spearman's rank correlation study between the ranks derived from the three approaches showed a favorable association between these methods.

Keywords: Online Learning, Ensemble Methods, RIDIT, TOPSIS, RII

Introduction

Recent technology-based learning approaches have greatly enhanced the teaching-learning process and transformed the educational landscape. Students' desire to study anywhere and anytime has increased a great deal due to these changes. Online Teaching-Learning (OTL) has become increasingly popular with more and more students and teachers engaging in it, especially after the COVID-19 Pandemic (Zhu et al., 2024). It is interesting and important to get insights into the factors that influence OTL from the perspective of all stakeholders.

Student involvement is the main goal of education as it contributes towards their overall growth and success. OTL offers several advantages for the same, such as remote accessibility to quality education, ease and flexibility of anytime-anywhere learning, increased control over the environment, and cost savings without compromising the quality of instruction. OTL resources have the potential to help in addressing the social and economic disparities among students.

Blended learning as well as OTL pose new challenges to the education system. It is important to assess the application and integration of technology to enhance all facets of education. A major problem for online learning can be technological hiccups that ruin the learning process (Sholihah et al., 2025). The excellence of OTL depends on the quality of the online education platforms, instructors, and resources available for teaching-learning, among other aspects.

The impact of virtual learning frequently depends on variables such as how it is implemented and the unique needs of each learner. OTL frequently results in isolation among students due to the lack of in-person interaction with peers and teachers. A virtual course necessitates a high degree of discipline and self-motivation. Online learning's efficacy can differ greatly from person to person as it is difficult for some scholars to stay focused in a virtual setting. A less engaging experience may result from poorly constructed courses or absence of interactive components. Inadequate or unstable access to the internet and required technologies can often dampen learning. Studies such as (Khattar et al., 2020; Wu and Hsu, 2024) state that the active engagement of students in online classes is a matter of concern. The carefully premeditated design of online teaching is essential for its effectiveness. It must ensure inclusion, support, and participation. One way to handle some of the social and motivational problems is to try to combine OTL with in-person encounters whenever possible.

A study focused on the teachers' perspective on numerous elements influencing students' interest and participation in online classes is as in Grover et al. (2024). Using the same dataset (Jain et al., 2021), the current study, attempts to rank the numerous elements influencing students' interest and participation. It attempts to explore the problems that students face in virtual learning settings.

The key contributions of this research is the proposed ensemble method to amalgamate the findings of several statistical and decision-making tools, namely RIDIT, TOPSIS, and RII, to rank of the issues faced by students during online classes. The ensemble approach proposed by this study diminishes the biases of the individual approaches and results in a relatively moderated ranking of alternatives.

Related Work

A thorough investigation of the OTL in the United States and Africa was conducted by Adeniyi et al. (2024). According to their research, e-learning has revolutionized access to higher education in the United States. The flexibility of e-learning allows people to pursue higher education without interfering with their everyday lives; this is especially beneficial for working professionals, parents, and individuals with other responsibilities. MOOCs and online degree programs have increased accessibility to education for anyone who may have a lack of time, money, or geographical limitations. While there exist several prospects for improvement in e-learning platforms, their flexibility and accessibility in higher education in Africa, their widespread adoption, and effectiveness depends on addressing issues such as technological infrastructure, economic inequality, and educational policy. According to the authors of Christiawan et al. (2020); Haron et al. (2021); Chogyel et al. (2021), lack of internet and unavailability of digital equipment are the biggest hurdles faced by students for online learning.

Google Meet, Microsoft Teams, Skype, and Zoom were the four well-known e-learning platforms that Akargöl et al. (2024) thoroughly analyzed using the Pythagorean Fuzzy Analytic Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approaches. The study creates a clear framework for the assessment procedure by employing the AHP model to organize and rank a variety of criteria. These platforms were then ranked using the Pythagorean Fuzzy TOPSIS technique by their overall performance in comparison to the specified criteria. The findings of this study allow academic institutions to customize the e-learning platform they choose to meet the specific needs of their curricula.

Silva et al. (2024) ranked Brazilian Air Force instructors using TOPSIS and determined criteria weights using the AHP. Their goal was to improve and expedite the selection process by making it more dependable, efficient, and less subjective. According to the results, those who were closer to the Positive Ideal Solution (PIS) were given positive signals, but those who were closer to the Negative Ideal Solution (NIS) were turned down. The hybrid AHP-TOPSIS method successfully ranked candidates and sped up the procedure. Wang et al. (2022) used entropy to assign importance to various parameters and TOPSIS to create a ranking for private higher universities in Vietnam.

A study by Akargöl et al. (2024) on Pythagorean Fuzzy AHP and TOPSIS methods, is an analysis of 4 major e-learning platforms, Google Meet, Microsoft Teams, Skype, and Zoom. The authors used Pythagorean fuzzy weighted averaging for the above study to rank these 4 e-learning platforms based on 10 criteria. The criteria considered include secure examination, knowledge transfer, adaptability, compatibility, recording of results, and customization. From training methods with user access to extensibility, the criteria focus on digital learning in higher education using linguistic variables.

Selecting an effective e-learning platform for high-quality online instruction involves all stakeholders, namely, instructors, students, and administrators of universities. The e-learning platform selection was approached as a complex Multi-Criteria Decision-Making (MCDM) problem by Ma et al. (2024). Based on the fuzzy analytic hierarchy process (FAHP) and the assessment based on Euclidean Distance from the Average Solution (EDAS) method to choose the best e-learning platform, researchers suggested a new hybrid MCDM approach. Comparing the proposed approach with two other traditional evaluation models, three real-world examples from China's e-learning platform evaluation demonstrated the superiority and applicability of the suggested methodology. The FAHP method was used Naveed et al. (2020) to study various factors affecting the web-based method of learning.

Youssef and Saleem (2023) believe that the quality of an institution can be enhanced by evaluating the performance of all stakeholders- i.e., students, teachers, administration, and infrastructure. They used a hybrid MCDM to determine the important variables responsible for enhancing the quality.

Dataset Used

This work uses the Covid-19 Go Away 2021 (C-19GA21) dataset which was originally collected via the survey for the study by Jain et al. (2022). Social media was used to collect the data via a Google form floated to the respondents during the period 4 April 2021 to 26 April 2021. The methodology used was snowball sampling. During COVID-19 these students had been taking online classes for more than a year. The data has 51 attributes of each of the 683 students in the dataset. The data has no missing elements. The attributes in the dataset relate to: "Basic demographic information like age, gender, nationality, state/ union territory, nature of institute, age group of participants, subjects taught/ learnt. Information related to connectivity, resources, queries related to teaching-learning activities such as time spent on screen, platforms used, communication methods, attendance in online classes, reasons for non-participation, obstacles encountered and learning experience of students in online classes etc. One more set of queries focused on emotional and behavioral aspects". The institutional diversity of the participants is as shown in Fig. 1. Figure 2 shows that the participants of the survey were residing in almost all regions of India during the lockdown. Further Fig. 3 depicts the age group they belong to, 66% of them were undergraduate students. The Cronbach's alpha for C-19GA21 is 0.81549. This ascertains that the dataset is reliable, consistent and robust.

Criteria and Alternatives

This paper ranks the alternatives for two criteria. Criterion I has alternatives (Q1 to Q13) based on query 23, and Criterion II has alternatives (Q1 to Q5) based on query 27 of the dataset C-19GA21.

The following section discusses in detail the criteria chosen for this study and the background of the alternatives therein.

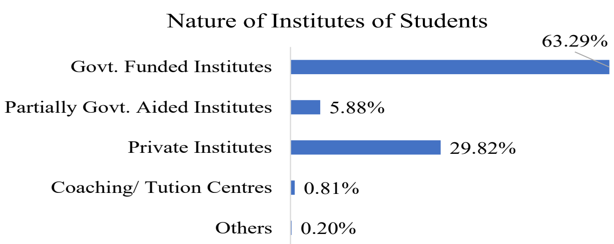

Fig. 1: Institutional Diversity of Students

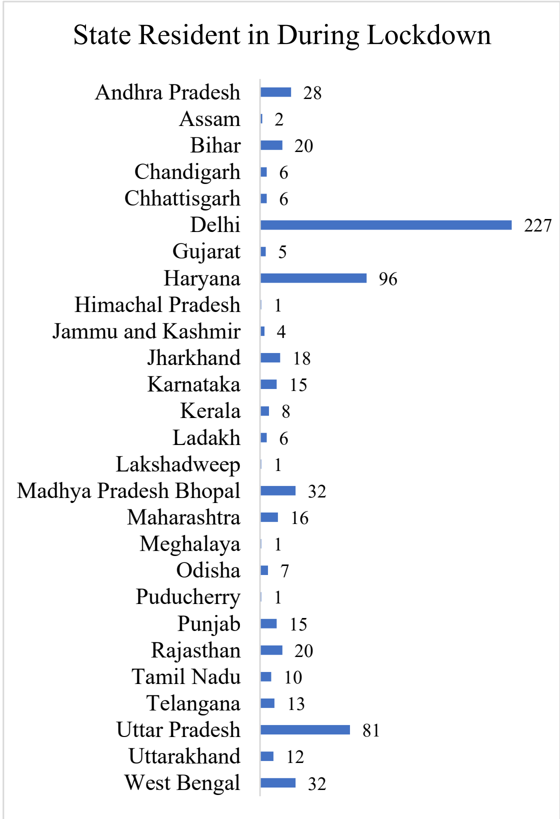

Fig. 2: Survey participants location in during Lockdown

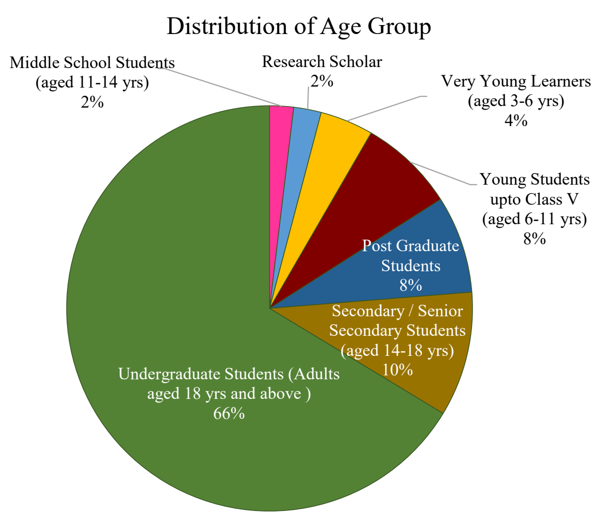

Fig. 3: Age group of Participants

Criterion I: Non-Participation of Students in Online Classes

The amount and type of exposure determine whether screen time has beneficial or detrimental impacts on health. Excessive screen time shows various physical health effects, including changed sleep patterns, behavioral changes, and health issues such as overweightness. Increased screen usage has been associated with longer sleep onset delays, shorter sleep durations, and lower sleep efficiency (Boone et al., 2007; Christensen et al., 2016). Students who took lessons online spent more time in front of screens, which had an impact on their general health. Mehta et al. (2023) conducted a study across medical colleges in Delhi to evaluate the effects of increased screen time on the physical and mental health of students. The outcome revealed that most students suffered from increased watery eyes, extreme sensitivity to light, dry eyes, redness, and itching in their eyes, as well as generalized anxiety and depression.

In an online classroom, the use of cameras is crucial from building community to the proof of attendance. It helps teachers interact with students more readily, monitor performance, communicate, and connect. It has been observed that students turn off their cameras during e-sessions largely due to comfort, concern about appearance, privacy, and poor internet connections (Castelli and Sarvary, 2021). In an online class with teacher's cameras on, many pupils gain from the enthusiasm and focus that facial expressions and energy can bring.

Academic performance and the overall well-being of students can be negatively impacted by the problems of distractions and absenteeism. Low attendance can lead to a variety of negative outcomes, including student reports, decreased knowledge creation, hampered educational quality, and compromised individual performance (Martínez-Serna et al., 2024). Distractions in the classroom can be recognized by students by observing things like cell phone use, side talk, multitasking, untidy workstations, or outside noise (Aivaz and Teodorescu, 2022).

Most teenage students have been battling boredom, particularly during the pandemic. There are several reasons for dullness, including the fact that they are not being pushed enough, the teaching strategies do not fit their preferred learning style, they might have a mental illness or learning disability, or they are just disengaged from the material and uninspired by their surroundings (Khattar et al., 2020). Larabi-Marie-Sainte et al. (2021) illustrate how students' academic performance is affected by absences and scheduling strategies. By planning the day, assigning tasks, and reducing disagreements, a timetable can make online classes go more easily and effectively.

A well-prepared study material can aid scholars in comprehending concepts and help them retain knowledge; these resources become more important in the case of remote classes held in emergent situations. Lesson recordings, instructor explanations, instructional materials, and online demonstrations are among the most important learning resources for students (Balderas-Solís et al., 2022). One of the most prevalent technological concerns in online learning is connectivity. From erratic networks to insufficient bandwidth, these issues can seriously impair the educational process. Poor internet connectivity puts a lot of obstacles in the way of students in rural locations. OBE (Open Book Exams) are a considerable departure from customary exams and require students to be able to apply or analyze knowledge and content rather than just memorize it to pass. This implies that students will not be able to learn the material by memorization, thus, they must study and organize themselves (Alghamdi, 2024).

Effective teaching requires several different abilities, such as patience, time management, and communication. For virtual classes, the instructor must have not only subject matter expertise but also technical proficiency, creative ability, administrative and organizational skills, and linguistic aptitude (Mehrotra et al., 2022). In the classroom, encouragement is a very potent tool. By living up to the conviction that every student has the potential and capacity to achieve their goals, educators and parents can foster a culture of hope. Both teachers and students may find online teaching and learning (OTL) exhausting, particularly when it involves extended classes; students often claim to be worn out. Several factors, including minimal human connection, prolonged screen time, and a lack of physical activity, contribute to OTL fatigue. Online tiredness and academic performance are negatively correlated; greater exhaustion results in worse academic performance (Alarabiat, 2024).

The divergent stacked bar charts alternatives of criterion I are as represented in Fig. 4.

Criterion II: Learning Experience of Students in Online Classes

As support from each other unconditionally, pals become your second family while you're a student. Developing close bonds with fellow students not only improves the academic experience overall but also fosters vital life skills like empathy, collaboration, and communication. Feeling cut off from friends can take many forms, such as feeling alone even in social situations, feeling misinterpreted, or as though no one understands you. Additionally, you may have a sense of emotional emptiness or low energy when interacting with people. Home quarantine, physical distancing, and school closures have led to missed social connections in an unprecedented sway (Parent et al., 2021). A personal regimen can assist you in reaching your objectives and in feeling content and healthy in a variety of ways, such as stress reduction, improved sleep, time management, and maintaining focus. Aside from emotions of bewilderment, missing your daily routine might lead to tension, anxiety, and a lack of focus.

Students benefit from flexibility, having more free time, and being able to learn at their own speed when they

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take classes online. Training focused on cognitive outcomes is not effectively accomplished through online learning. Some students may lack the motivation to learn with technology. Learners cannot connect with peers, experts, or other content through online learning. In-person classes facilitate group projects, discussions, and casual conversations before and after class; however, online programs need more effort in terms of interpersonal communication and connection building. Attending virtual classes does not allow students to build relationships with their fellow students the way they would in physical classrooms. Initially, parents and children may both be thrilled to witness the digital world in online education mode.

Particularly, the students are excited to attend class from home. But as time passes, parents often worry about their children spending too much time on screens, and students also get anxious about the same thing. However, the demand for distance education is increasing.

The divergent stacked bar charts for alternatives of criterion II are as represented in Fig. 5.

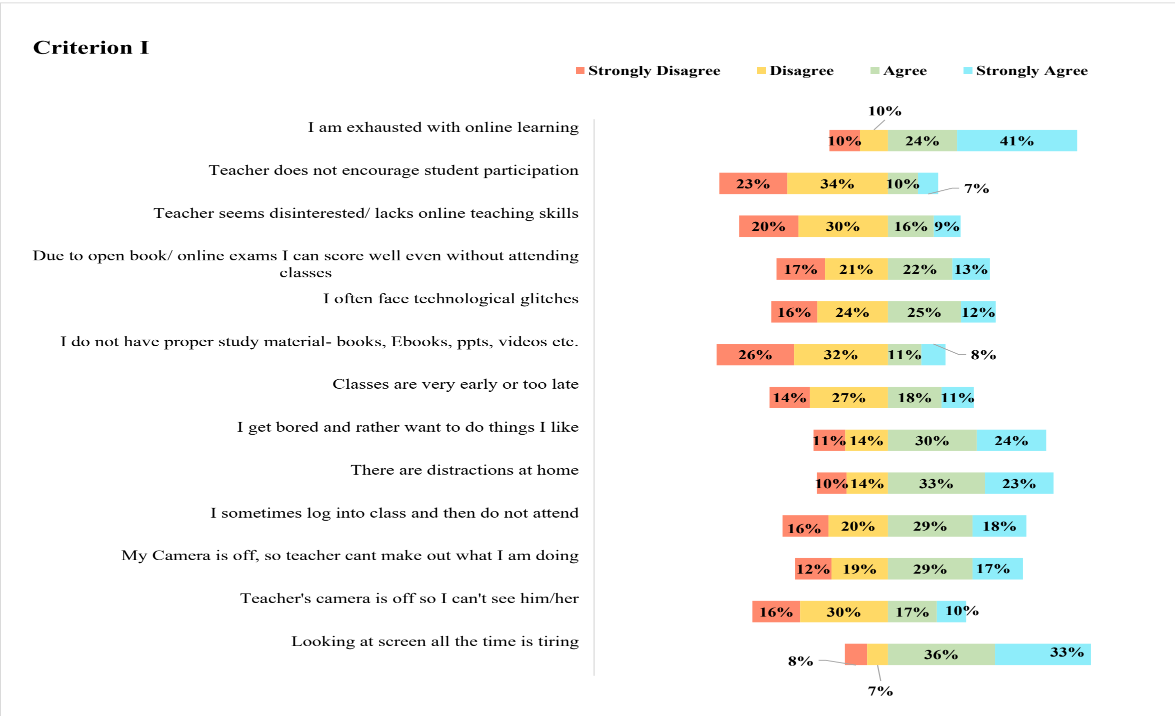

Fig. 4: Divergent stacked bars for alternatives for non-participation of students in online classes (Criterion I)

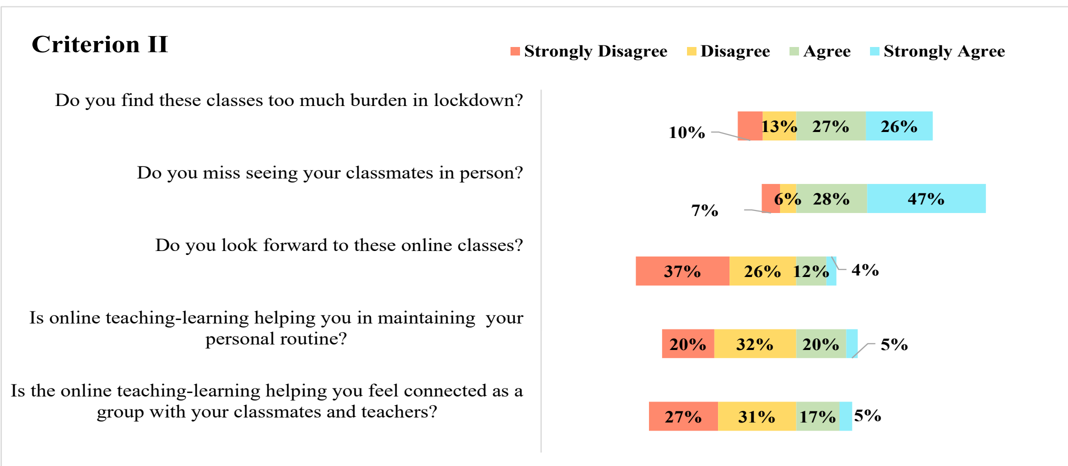

Fig. 5: Divergent stacked bar for Learning experience of students in online classes (Criterion II)

Theoretical Concepts

The suggested methodology incorporates a number of MCDM techniques in order to reduce the uncertainties brought forth by these techniques. Data were then evaluated using three established MCDM techniques: TOPSIS, RII and RIDIT analysis. TOPSIS is a well-known technique that has been utilized to prioritize the aspects and enhance the service quality of different facilities. TOPSIS is particularly advantageous as it can manage weighted criteria, permitting attributes with different levels of significance to be ranked precisely. TOPSIS has the benefit of being straightforward and producing an indisputable preference classification. On the other hand, using the advanced methodology like RIDIT analysis complements TOPSIS because it is a distribution-based method to ascertain appropriate scores to the ordered categories. RIDIT is apt for inspecting Likert-scale survey outcomes as it ranks attributes by comparing responses to a reference distribution, without assuming that the categories are equally spaced. RII is employed for ranking of factors or attributes based on respondents' ratings usually collected via Likert scale survey. It provides a simple measure of perceived importance or impact of each of them. TOPSIS, RIDIT and RII offers a rational integration of prioritizing objectives in comparison to other MCDM methods like AHP and Fuzzy TOPSIS which are either more complex or relies on judgement. When combined, these techniques guarantee a thorough examination by utilizing RIDIT's and RII's emphasis on response distribution and consensus and TOPSIS's capacity to find optimal solutions, making them the best instruments for assessing the factors influencing OTL. Thereafter ensemble method of majority voting is used to aggregate the results obtained from the three ranking methods. The Spearman Rank Correlation is further used to compare the results of different techniques in order to identify the contributing components of OTL.

The following section discusses the methods- RIDIT, TOPSIS, RII and ensemble that are used to rank the alternatives for the two criteria in this paper.

Ridit

Bross coined the term RIDIT in 1958 (Youssef and Saleem, 2023). It is a statistical technique for examining ordered qualitative measures. RIDIT analysis finds use in several domains, such as behavioural research, human psychology, and corporate management, etc. It is an extremely effective method for analyzing Likert scale data since it makes no assumptions about the distribution under study (Fleiss et al., 2003; Koo and Yang, 2025; Uwawunkonye, 2013). This feature is especially useful in statistical analysis for items having ratings for three or more points, as well as for indexes that are composed of many items with ratings derived from universal ratings (Beder and Heim, 1990). Arranging Likert scale items in ascending or descending order depending on their importance is done using the results of the RIDIT analysis.

Let us assume that the scale consists of items and sorted categories, listed from most preferred to least preferred:

1. Generate a reference matrix from the Likert scale data set
2. Compute frequency for each category of responses
3. Determine the midpoint cumulative frequency F_j for every response

$$F_1 = \frac{1}{2} f_1, F_j = \frac{1}{2} f_j + \sum_{k=1}^{j-1} f_k \,, j = 1,2, \ldots., n \qquad (1)$$

4. Compute the RIDIT value for each category of responses in the reference data set $R_j = \frac{F_j}{N}\,, j = 1, 2, \ldots, n.$ N represents the total responses from the Likert scale survey
5. If π_{ij} represents the frequency of category j for scale item, i then the $\pi_i = \sum_{k=1}^{n} \pi_{ij}$ is the total frequency sum for the scale item i
6. Generate values corresponding to each category of scale items:

$$r_{ij} = \frac{R_j \times \pi_{ij}}{\pi_i}, i = 1,2, \ldots, m.$$

7. Calculate mean ρ_i for each Likert scale item given by $\rho_i = \sum_{k=1}^{n} r_{ik}, i = 1, \cdots, n$
8. Rank the alternatives based on RIDIT mean values

TOPSIS

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), proposed by Hwang and Yoon, is one of the widespread methods for comparing and ranking the options in MADM. Its foundation lies in the idea of calculating the separation between the best possible solutions and their alternatives. The alternatives are graded depending upon how near or far they are from the perfect option. The ideal way to characterize the student's viewpoint of the factors influencing OTL in terms of language variables would be to use the terms "strongly disagree," "disagree," "neither agree nor disagree," agree, and "strongly agree." These can be rated on a scale from 1 to 9, where 9 indicates significant agreement.

Linguistic Conversion Scale

To translate the linguistic concepts into crisp numbers, a conversion scale is used. Odd numbers are used as the consent level on the scale (1, 3, 5, 7, 9), as depicted in Table 1.

Table 1: Ratings of linguistic variables

Alternative	Scale
Strongly disagree (SD)	1
Disagree (D)	3
Neither agree nor disagree (NAND)	5
Agree (A)	7
Strongly agree (SA)	9

The procedure used to rank the alternatives using TOPSIS is as follows:

1) Step 1: Convert linguistic variables into clear numerical values as described in Table 1
2) Step 2: Generate the decision matrix C with m decision makers and n alternatives for each criterion
3) Step 3: Determine the normalized decision matrix

$$\Delta = \begin{bmatrix} \Delta_{11} & \cdots & \Delta_{1n} \\ \vdots & \ddots & \vdots \\ \Delta_{m1} & \cdots & \Delta_{mn} \end{bmatrix}$$

Where:

$$\Delta_{ij} = \frac{c_{ij}}{\sqrt{\sum_{k=1}^{m} c_{kj}{}^2}} \tag{1}$$

Step 4: Construct weighted normalized decision matrix $\delta = [\tilde{\delta}_{ij}]$ where $\delta_{ij} = w_j * \Delta_{ij}$:

$$\text{with } w_j = \frac{1}{n}; \forall\, j = 1, \dots, n \tag{2}$$

Step 5: Determine the ideal best solution δ_j^+ and ideal worst solution δ_j^-:

$$\delta_j^+ = max_i\{\delta_{ij}\}; i = 1,2,\cdots,m;\ j = 1,2,\cdots,n$$
$$\delta_j^- = min_i\{\delta_{ij}\}; i = 1,2,\cdots,m;\ j = 1,2,\cdots,n \tag{3}$$

Step 6: Determine the distance of each alternative from the ideal worst value S_i^- and the ideal best value S_i^+ as:

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(\delta_{ij} - \delta_j^+)^2}\ \forall\, i = 1, \dots, m; j = 1, \dots, n$$
$$S_i^- = \sqrt{\sum_{j=1}^{n}(\delta_{ij} - \delta_j^-)^2}\ \forall\, i = 1, \dots, m; j = 1, \dots, n \tag{4}$$

Step 7: Find the closeness coefficient for each alternative:

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{5}$$

Step 8: Rank the alternatives in decreasing order of the score obtained.

Relative Importance Index (RII)

The RII is the equivalent contribution of each predictor because of its combined influence with other variables in the regression equation and also its direct effect, i.e., correlation with the criteria (Johnson and Lebreton, 2004; Kinemo, 2024).

RII is a tool for evaluating the significance of various criteria or factors based on participants' responses. It is widely used for figuring out which indications, out of a set of survey questionnaire replies, are the most pertinent. Likert scales can be used to rate indicators, and the RII can be used to prioritize them. In these situations, the respondent's weighting of each component, denoted by W, equals the points on the Likert scale. Using the relative relevance index analysis, the criteria are ranked according to their respective importance. Relative relevance index analysis is a useful approach for prioritizing indicators scored on Likert scales and for determining the majority of significant criteria based on participant replies (Rooshdi et al., 2018).

The RII approach is widely used to analyze survey data obtained via the use of response scales in questionnaires. The analyst choosing RII aims to generate an index that can ordinally arrange those variables being studied. The RII value is a number where a factor with a higher RII value is more significant. Researchers often employ non-parametric RII method to analyze structured responses to questionnaires for ordinal data assessment of attitudes (Johnson and Lebreton, 2004):

$$r = \sum_{i=1}^{n} \frac{w_i\, n_i}{NA} = \frac{5\, n_5 + 4\, n_4 + 3\, n_3 + 2\, n_2 + 1\, n_1}{5\, N} \tag{6}$$

Where: w_i is the respondent weight to the i^{th} factor, $i = 1, \dots, 5$.

n_1 refers to the number of respondents for Strongly Disagree, n_2 refers to the number of respondents for Disagree, n_3 refers to the number of respondents for Neither Agree nor Disagree, n_4 denotes the number of respondents for Agree, n_5 denotes the number of respondents for Strongly Agree, N is the total no. of respondents. A is the highest weight, which is 5 in our case.

Ensemble Method

Ensemble methods use multiple models to increase the accuracy of findings. Amalgamating the outcomes of the individual models into an outcome of the ensemble method often leads to more accurate and reliable results. Majority voting is one of the popular ensemble techniques. With majority voting, the alternative that obtains the maximum number of votes is chosen as the winner. Each model in the ensemble ranks the alternative as per its algorithm. The most frequent rank for the alternative determines the ensemble rank for the alternative. This paper uses the majority voting as the ensemble technique that combines the outcomes of RIDIT, TOPSIS and RII methods.

Methodology

The proposed study uses three ranking tools, RIDIT, TOPSIS, and RII on the alternatives of the above two criteria. It further employs majority voting ensemble method to rank the alternatives.

The stepwise outcome of the methods applied in this study are explained below.

Ranking Using RIDIT

RIDIT computations were done on Criterion I based on the discussion in section 4.1. The outcome of steps 1 to 5 computed for Criterion I and Criterion II are shown in Table 2. The outcome of steps 6 to 8 computed for Criterion I and Criterion II are shown in Table 3.

Ranking Using TOPSIS

The TOPSIS value for alternatives of Criterion I and Criterion II were computed in accordance with the discussion in Section 4.2. The outcome of these computations for Criterion I and Criterion II are shown in Tables 4-6.

Step 1: The linguistic variables were converted to numerical values as described in Table 1.
Step 2: The decision matrix was generated with:

- 683 decision makers and 13 alternatives for Criterion I
- 683 decision makers and 5 alternatives for Criterion II

The outcome of this step is as illustrated in Table 4.

Step 3: The decision matrix was normalized, as illustrated in Table 5.

Step 4: The weighted normalized decision matrix after multiplying the normalized decision matrix with weights is as illustrated in Tables 6-7.

Steps 5-8: The ideal best solution and ideal worst solution is calculated from the weighted normalized decision matrix for each decision maker as in Equation 4.2.3. These are then used to find the distance of each alternative from the ideal worst value and the ideal best value using Equation 4.2.4. The 'Si^{+}' and 'Si^{-}' are used to compute the Closeness Coefficient (CC) using Equation 4.2.5.

Table 2: Outcome of RIDIT for Steps 1 to 5 for alternatives of Criterion I and Criterion II

Criterion I: Alternatives		SD	D	NAND	A	SA
	Q1	52	48	111	249	223
	Q2	111	204	186	114	68
	Q3	85	131	153	197	117
	Q4	107	138	116	197	125
	Q5	69	96	133	226	159
	Q6	74	99	142	207	161
	Q7	94	181	208	125	75
	Q8	180	218	151	78	56
	Q9	107	164	161	170	81
	Q10	113	146	187	150	87
	Q11	138	208	168	107	62
	Q12	158	234	174	70	47
	Q13	71	65	107	161	279
f_j	f_j	1359	1932	1997	2051	1540
$f_j/2$	$f_j/2$	679.5	966	998.5	1025.5	770
F_j	F_j	679.5	2325	4289.5	6313.5	9649
$R_j=F_j/n$, n = 683	$R_j=F_j/n$, n = 683	0.995	3.404	6.280	9.244	14.127
Criterion II: Alternatives		**SD**	**D**	**NAND**	**A**	**SA**
	Q1	185	209	139	116	34
	Q2	140	219	159	134	31
	Q3	251	178	146	81	27
	Q4	49	43	83	190	318
	Q5	67	89	161	187	179
f_j	f_j	692	738	688	708	589
$f_j/2$	$f_j/2$	346	369	344	354	294.5
F_j	F_j	346	1061	1774	2472	3120.5
$R_j=F_j/n$, n = 683	$R_j=F_j/n$, n = 683	0.507	1.553	2.597	3.619	4.569

Table 3: Outcome of RIDIT for Steps 6, 7, and 8 for alternatives Criterion I and II

Criterion I: Alternatives Q1 to Q13		SD (r_{ij})	D	NAND	A	SA	RIDIT MEAN (ρ_i)	RIDIT RANK
Q1	Looking at screen all the time is tiring	0.0757	0.2392	1.0207	3.37	4.6126	9.3182	2
Q2	Teacher's camera is off so I can't see him/her	0.1617	1.0167	1.7103	1.5429	1.4065	5.8382	10
Q3	My Camera is off, so teacher can't make out what I am doing	0.1238	0.6529	1.4069	2.6662	2.4201	7.2699	5
Q4	I sometimes log into class and then do not attend	0.1559	0.6878	1.0667	2.6662	2.5855	7.1621	6
Q5	There are distractions at home	0.1005	0.4785	1.223	3.0587	3.2888	8.1495	3
Q6	I get bored and rather want to do things I like	0.1078	0.4934	1.3057	2.8016	3.3302	8.0387	4
Q7	Classes are very early or too late	0.1369	0.9021	1.9126	1.6918	1.5513	6.1947	9
Q8	I do not have proper study material- books, Ebooks, ppts, videos etc.	0.2622	1.0865	1.3885	1.0557	1.1583	4.9512	12
Q9	I often face technological glitches	0.1559	0.8174	1.4804	2.3008	1.6754	6.4299	8
Q10	Due to open book/ online exams I can score well even without attending classes	0.1646	0.7277	1.7195	2.0301	1.7995	6.4414	7
Q11	Teacher seems disinterested/ lacks online teaching skills	0.201	1.0367	1.5448	1.4481	1.2824	5.5131	11
Q12	Teacher does not encourage student participation	0.2301	1.1663	1.6	0.9474	0.9722	4.9159	13
Q13	I am exhausted with online learning	0.1034	0.324	0.9839	2.179	5.7709	9.3612	1
Criterion II: Alternatives Q1 to Q5		**SD (r_{ij})**	**D**	**NAND**	**A**	**SA**	**RIDIT MEAN (ρ_i)**	**RIDIT RANK**
Q1	Is the online teaching-learning helping you feel connected as a group with your classmates and teachers?	0.1372	0.4754	0.5286	0.6147	0.2274	1.9833	4
Q2	Is online teaching-learning helping you in maintaining your personal routine?	0.1038	0.4981	0.6047	0.7101	0.2074	2.1241	3
Q3	Do you look forward to these online classes?	0.1862	0.4048	0.5552	0.4292	0.1806	1.7561	5
Q4	Do you miss seeing your classmates in person?	0.0363	0.0978	0.3156	1.0068	2.1272	3.5838	1
Q5	Do you find these classes too much burden in lockdown?	0.0497	0.2024	0.6123	0.9909	1.1974	3.0527	2

Table 4: Outcome of TOPSIS for Step 2: Decision Matrix for alternatives of Criterion I and Criterion II

Criterion I: Alternatives		Decision Maker's response for Criterion I																			
Q1	Looking at screen all the time is tiring	9	7	9	9	7	9	9	9	...	1	1	9	9	9	3	9	9	5	1
Q2	Teacher's camera is off so I can't see him/her	7	7	3	9	5	3	3	7	...	1	1	5	5	5	3	7	9	5	1
Q3	My Camera is off, so teacher cant make out wha...	9	7	7	9	5	5	7	7	...	1	1	1	1	7	3	9	9	5	1
Q4	I sometimes log into class and then do not attend	7	7	7	9	7	7	1	7	...	5	5	1	1	9	5	9	9	5	1
Q5	There are distractions at home	7	7	3	9	7	7	3	7	...	1	1	1	1	9	1	9	9	1	1
Q6	I get bored and rather want to do things I like	7	7	9	9	7	9	5	9	...	5	5	9	9	5	5	9	9	3	1
Q7	Classes are very early or too late	3	5	1	7	9	3	7	3	...	1	1	7	7	7	1	9	9	3	1
Q8	I do not have proper study material- books, Eb...	1	3	3	5	1	3	1	3	...	5	5	7	7	5	3	7	9	3	1
Q9	I often face technological glitches	1	3	3	5	1	9	5	7	...	1	1	7	7	5	5	9	9	3	1
Q10	Due to open book/ online exams I can score wel...	7	7	3	9	1	7	1	3	...	1	1	3	3	5	3	1	9	1	1
Q11	Teacher seems disinterested/ lacks online teac...	3	7	1	9	1	7	1	3	...	1	1	3	3	1	3	3	9	5	1
Q12	Teacher does not encourage student participation	1	5	1	9	1	3	3	5	...	1	1	9	9	5	3	7	9	3	1
Q13	I am exhausted with online learning	7	9	9	9	7	9	9	7	...	1	1	7	7	9	5	9	9	5	1
Criterion II: Alternatives		**Decision Maker's response for Criterion II**																			
Q1	Is the online teaching-learning helping you fe...	1	1	1	3	1	1	3	5	...	1	1	3	3	1	1	3	9	1	1
Q2	Is online teaching-learning helping you in mai...	3	1	7	3	3	1	5	3	...	1	1	5	5	1	5	1	9	3	1
Q3	Do you look forward to these online classes?	1	1	3	1	1	1	1	5	...	1	1	1	1	1	3	1	9	3	1
Q4	Do you miss seeing your classmates in person?	9	7	9	9	9	9	9	7	...	5	5	7	7	5	1	9	9	5	1
Q5	Do you find these classes too much burden in l...	7	9	9	7	5	9	9	5	...	5	5	7	7	7	3	9	9	5	1

Table 5: Outcome of TOPSIS for Step 3: Normalized Decision Matrix for alternatives of Criterion I and Criterion II

Criterion I: Alternatives		Decision Maker's response for Criterion I																			
Q1	Looking at screen all the time is tiring	0.512	0.447	0.641	0.447	0.499	0.617	0.737	0.541	...	0.186	0.186	0.862	0.862	0.505	0.412	0.466	0.447	0.498	0.447
Q2	Teacher's camera is off so I can't see him/her	0.398	0.447	0.214	0.447	0.356	0.206	0.246	0.421	...	0.186	0.186	0.479	0.479	0.281	0.412	0.362	0.447	0.498	0.447
Q3	My Camera is off, so teacher cant make out wha...	0.512	0.447	0.499	0.447	0.356	0.343	0.573	0.421	...	0.186	0.186	0.096	0.096	0.393	0.412	0.466	0.447	0.498	0.447
Q4	I sometimes log into class and then do not attend	0.398	0.447	0.499	0.447	0.499	0.48	0.082	0.421	...	0.928	0.928	0.096	0.096	0.505	0.687	0.466	0.447	0.498	0.447
Q5	There are distractions at home	0.398	0.447	0.214	0.447	0.499	0.48	0.246	0.421	...	0.186	0.186	0.096	0.096	0.505	0.137	0.466	0.447	0.1	0.447
Q6	I get bored and rather want to do things I like	0.398	0.447	0.641	0.447	0.499	0.617	0.41	0.541	...	0.928	0.928	0.862	0.862	0.281	0.687	0.466	0.447	0.299	0.447
Q7	Classes are very early or too late	0.171	0.319	0.071	0.348	0.641	0.206	0.573	0.18	...	0.186	0.186	0.67	0.67	0.393	0.137	0.466	0.447	0.299	0.447
Q8	I do not have proper study material- books, Eb...	0.057	0.192	0.214	0.248	0.071	0.206	0.082	0.18	...	0.928	0.928	0.67	0.67	0.281	0.412	0.362	0.447	0.299	0.447
Q9	I often face technological glitches	0.057	0.192	0.214	0.248	0.071	0.617	0.41	0.421	...	0.186	0.186	0.67	0.67	0.281	0.687	0.466	0.447	0.299	0.447
Q10	Due to open book/ online exams I can score wel...	0.398	0.447	0.214	0.447	0.071	0.48	0.082	0.18	...	0.186	0.186	0.287	0.287	0.281	0.412	0.052	0.447	0.1	0.447
Q11	Teacher seems disinterested/ lacks online teac...	0.171	0.447	0.071	0.447	0.071	0.48	0.082	0.18	...	0.186	0.186	0.287	0.287	0.056	0.412	0.155	0.447	0.498	0.447
Q12	Teacher does not encourage student participation	0.057	0.319	0.071	0.447	0.071	0.206	0.246	0.3	...	0.186	0.186	0.862	0.862	0.281	0.412	0.362	0.447	0.299	0.447
Q13	I am exhausted with online learning	0.398	0.575	0.641	0.447	0.499	0.617	0.737	0.421	...	0.186	0.186	0.67	0.67	0.505	0.687	0.466	0.447	0.498	0.447
Criterion II: Alternatives		**Decision Maker's response for Criterion II**																			
Q1	Is the online teaching-learning helping you fe...	0.084	0.087	0.067	0.246	0.092	0.078	0.214	0.434	...	0.137	0.137	0.26	0.26	0.114	0.149	0.228	0.447	0.12	0.447
Q2	Is online teaching-learning helping you in mai...	0.253	0.087	0.471	0.246	0.277	0.078	0.356	0.26	...	0.137	0.137	0.434	0.434	0.114	0.745	0.076	0.447	0.361	0.447
Q3	Do you look forward to these online classes?	0.084	0.087	0.202	0.082	0.092	0.078	0.071	0.434	...	0.137	0.137	0.087	0.087	0.114	0.447	0.076	0.447	0.361	0.447
Q4	Do you miss seeing your classmates in person?	0.758	0.607	0.605	0.737	0.832	0.701	0.641	0.607	...	0.687	0.687	0.607	0.607	0.57	0.149	0.684	0.447	0.602	0.447
Q5	Do you find these classes too much burden in l...	0.59	0.78	0.605	0.573	0.462	0.701	0.641	0.434	...	0.687	0.687	0.607	0.607	0.798	0.447	0.684	0.447	0.602	0.447

Table 6: Outcome of TOPSIS for Step 4: Weighted Normalized Decision Matrix for alternatives of Criterion I and Criterion II

Criterion I: Alternatives		Decision Maker's response for Criterion I																			
Q1	Looking at screen all the time is tiring	0.064	0.056	0.08	0.056	0.062	0.077	0.092	0.068	...	0.023	0.023	0.108	0.108	0.063	0.052	0.058	0.056	0.062	0.056
Q2	Teacher's camera is off so I can't see him/her	0.05	0.056	0.027	0.056	0.044	0.026	0.031	0.053	...	0.023	0.023	0.06	0.06	0.035	0.052	0.045	0.056	0.062	0.056
Q3	My Camera is off, so teacher cant make out wha...	0.064	0.056	0.062	0.056	0.044	0.043	0.072	0.053	...	0.023	0.023	0.012	0.012	0.049	0.052	0.058	0.056	0.062	0.056
Q4	I sometimes log into class and then do not attend	0.05	0.056	0.062	0.056	0.062	0.06	0.01	0.053	...	0.116	0.116	0.012	0.012	0.063	0.086	0.058	0.056	0.062	0.056
Q5	There are distractions at home	0.05	0.056	0.027	0.056	0.062	0.06	0.031	0.053	...	0.023	0.023	0.012	0.012	0.063	0.017	0.058	0.056	0.012	0.056
Q6	I get bored and rather want to do things I like	0.05	0.056	0.08	0.056	0.062	0.077	0.051	0.068	...	0.116	0.116	0.108	0.108	0.035	0.086	0.058	0.056	0.037	0.056
Q7	Classes are very early or too late	0.021	0.04	0.009	0.044	0.08	0.026	0.072	0.022	...	0.023	0.023	0.084	0.084	0.049	0.017	0.058	0.056	0.037	0.056
Q8	I do not have proper study material- books, Eb...	0.007	0.024	0.027	0.031	0.009	0.026	0.01	0.022	...	0.116	0.116	0.084	0.084	0.035	0.052	0.045	0.056	0.037	0.056
Q9	I often face technological glitches	0.007	0.024	0.027	0.031	0.009	0.077	0.051	0.053	...	0.023	0.023	0.084	0.084	0.035	0.086	0.058	0.056	0.037	0.056
Q10	Due to open book/ online exams I can score wel...	0.05	0.056	0.027	0.056	0.009	0.06	0.01	0.022	...	0.023	0.023	0.036	0.036	0.035	0.052	0.006	0.056	0.012	0.056
Q11	Teacher seems disinterested/ lacks online teac...	0.021	0.056	0.009	0.056	0.009	0.06	0.01	0.022	...	0.023	0.023	0.036	0.036	0.007	0.052	0.019	0.056	0.062	0.056
Q12	Teacher does not encourage student participation	0.007	0.04	0.009	0.056	0.009	0.026	0.031	0.038	...	0.023	0.023	0.108	0.108	0.035	0.052	0.045	0.056	0.037	0.056
Q13	I am exhausted with online learning	0.05	0.072	0.08	0.056	0.062	0.077	0.092	0.053	...	0.023	0.023	0.084	0.084	0.063	0.086	0.058	0.056	0.062	0.056
Criterion II: Alternatives		**Decision Maker's response for Criterion II**																			
Q1	Is the online teaching-learning helping you fe...	0.01	0.011	0.008	0.031	0.012	0.01	0.027	0.054	...	0.017	0.017	0.032	0.032	0.014	0.019	0.028	0.056	0.015	0.056
Q2	Is online teaching-learning helping you in mai...	0.032	0.011	0.059	0.031	0.035	0.01	0.044	0.032	...	0.017	0.017	0.054	0.054	0.014	0.093	0.01	0.056	0.045	0.056
Q3	Do you look forward to these online classes?	0.01	0.011	0.025	0.01	0.012	0.01	0.009	0.054	...	0.017	0.017	0.011	0.011	0.014	0.056	0.01	0.056	0.045	0.056
Q4	Do you miss seeing your classmates in person?	0.095	0.076	0.076	0.092	0.104	0.088	0.08	0.076	...	0.086	0.086	0.076	0.076	0.071	0.019	0.086	0.056	0.075	0.056
Q5	Do you find these classes too much burden in l...	0.074	0.098	0.076	0.072	0.058	0.088	0.08	0.054	...	0.086	0.086	0.076	0.076	0.1	0.056	0.086	0.056	0.075	0.056

Table 7: Outcome of TOPSIS for Steps 5 to 8: Rank for alternatives of Criterion I and Criterion II

Criterion I: Alternatives (Q1 to Q13)		Si^+	Si^-	CC	Rank n=13
Q1	Looking at screen all the time is tiring	0.9975	1.2482	0.5558	2
Q2	Teacher's camera is off so I can't see him/her	1.3660	0.7755	0.3621	12
Q3	My Camera is off, so teacher cant make out what I am doing	1.2530	0.9466	0.4303	7
Q4	I sometimes log into class and then do not attend	1.2966	0.9254	0.4165	8
Q5	There are distractions at home	1.1283	1.0785	0.4887	4
Q6	I get bored and rather want to do things I like	1.1156	1.1133	0.4995	3
Q7	Classes are very early or too late	1.2662	0.8987	0.4151	9
Q8	I do not have proper study material- books, Ebooks, ppts, videos etc.	1.4173	0.7503	0.3461	13
Q9	I often face technological glitches	1.2101	0.9988	0.4522	6
Q10	Due to open book/ online exams I can score well even without attending classes	1.1735	1.0210	0.4652	5
Q11	Teacher seems disinterested/ lacks online teaching skills	1.2951	0.8859	0.4062	10
Q12	Teacher does not encourage student participation	1.3482	0.7882	0.3689	11
Q13	I am exhausted with online learning	0.8128	1.4195	0.6359	1
Criterion II: Alternatives (Q1 to Q5)		Si^+	Si^-	CC	Rank n=5

Criterion I: Alternatives (Q1 to Q13)		Si^{+}	Si^{-}	CC	Rank n=13
Q1	Is the online teaching-learning helping you feel connected as a group with your classmates and teachers?	1.3391	0.3284	0.6548	4
Q2	Is online teaching-learning helping you in maintaining your personal routine?	1.2616	0.3650	0.7251	3
Q3	Do you look forward to these online classes?	1.4279	0.2860	0.5721	5
Q4	Do you miss seeing your classmates in person?	0.5768	0.7174	1.4644	1
Q5	Do you find these classes too much burden in lockdown?	0.8526	0.5915	1.2343	2

Ranking Using RII

As discussed in section 4.3, the RII value for each alternative of Criterion I and Criterion II were computed using the equation 4.3.1. The outcome of this for the same is shown in Table 8.

Results and Discussion

We analyze and evaluate patterns and trends that affect students' health and their academic performance during e-classes. The emphasis on extensive screen time and the dearth of interaction are a key concern for students' mental and physical wellbeing.

The rankings of the alternatives for Criterion I and II using RIDIT, TOPSIS, and RII are displayed in Tables 3, 7, and 8. The results verify that these methods yield different ranks. For instance, for Criterion I: "Non-participation of students in online classes," the alternative with rank 1 for RIDIT and TOPSIS is "I am exhausted in online learning," while the number one ranking for the RII method is "Looking at the screen all the time is tiring." To get a single rank for each alternative in Criterion I and Criterion II, the ranks derived from the three methods RIDIT, TOPSIS, and RII are combined using the ensemble majority voting method. Using this approach, Table 9 lists the ranks for each alternative in Criterion I. The findings support that students become weary of online learning as the alternative with rank 1 for Criterion I is 'I am exhausted with online learning'. The second-ranked alternative 'Looking at screen all the time is tiring' claims that they become tired of staring at screens all the time. Additionally, the alternative 'There are distractions at home' is rated at rank 3. It is encouraging to note that there is no dearth of learning resources available to the students in virtual learning settings as the alternative 'I do not have proper study material- books, ebooks, ppts, videos etc.' is ranked last (rank 13) by this analysis. This indicates that the students have access to internet and other resources in general.

A similar analysis for Criterion II is also depicted in Table 9. It reveals that the students really miss seeing their classmates in person during online learning since the alternative 'Do you miss seeing your classmates in person?' gets the rank 1.

The rankings of the factors for this study derived from the three distinct analyses show a great deal of resemblance. The correlation between the calculated ranks is examined using Spearman rank-correlation. Spearman rank-correlation coefficient between the RIDIT and RII rankings is 0.923. The coefficient comparing the rankings from RIDIT, TOPSIS is 0.923 and the coefficient comparing the ranks from RIDIT, TOPSIS is 0.984. As a result, it can be said that there is a substantial positive correlation between the rankings derived from the three analytical techniques. The ensemble method offers a clear hierarchy of the obstacles faced by the students during OTL.

Table 8: Outcome of RII: Ranks of alternatives for Criterion I and Criterion II

Criterion I	$SD \times 1$	$D \times 2$	$NAND \times 3$	$A \times 4$	$SA \times 5$	Total R	$R \div (683 \times 5)$	RII Rank
Q1	52	96	333	996	1115	2592	0.759	1
Q2	111	408	558	456	340	1873	0.5485	10
Q3	85	262	459	788	585	2179	0.6381	5
Q4	107	276	348	788	625	2144	0.6278	6
Q5	69	192	399	904	795	2359	0.6908	3
Q6	74	198	426	828	805	2331	0.6826	4
Q7	94	362	624	500	375	1955	0.5725	9
Q8	180	436	453	312	280	1661	0.4864	13
Q9	107	328	483	680	405	2003	0.5865	7
Q10	113	292	561	600	435	2001	0.5859	8
Q11	138	416	504	428	310	1796	0.5259	11
Q12	158	468	522	280	235	1663	0.487	12
Q13	71	130	321	644	1395	2561	0.7499	2

Table 9: Ensemble Ranks for Alternatives of Criterion I and II

Criterion I: Alternatives		RIDIT Rank	TOPSIS Rank	RII Rank	Ensemble Method (Majority Voting)
Q1	Looking at screen all the time is tiring	2	1	2	2
Q2	Teacher's camera is off so I can't see him/her	10	10	12	10
Q3	My Camera is off, so teacher can't make out what I am doing	5	5	7	5
Q4	I sometimes log into class and then do not attend	6	6	8	6
Q5	There are distractions at home	3	3	4	3
Q6	I get bored and rather want to do things I like	4	4	3	4
Q7	Classes are very early or too late	9	9	9	9
Q8	I do not have proper study material- books, ebooks, ppts, videos etc.	12	13	13	13
Q9	I often face technological glitches	8	7	6	7
Q10	Due to open book/ online exams I can score well even without attending classes	7	8	5	7
Q11	Teacher seems disinterested/ lacks online teaching skills	11	11	10	11
Q12	Teacher does not encourage student participation	13	12	11	12
Q13	I am exhausted with online learning	1	2	1	1
Criterion II: Alternatives		**RIDIT Rank**	**TOPSIS Rank**	**RII Rank**	**Ensemble Method (Majority Voting)**
Q1	Is the online teaching-learning helping you feel connected as a group with your classmates and teachers?	4	4	4	4
Q2	Is online teaching-learning helping you in maintaining your personal routine?	3	3	3	3
Q3	Do you look forward to these online classes?	5	5	5	5
Q4	Do you miss seeing your classmates in person?	1	1	1	1
Q5	Do you find these classes too much burden in lockdown?	2	2	2	2

Conclusion

This study employs MCDM ranking algorithms to identify the obstacles faced by students that may hinder their ample participation in online classes. This data was collected during the COVID-19 lockdown. The use of statistical decision-making tools, namely RIDIT, TOPSIS, and RII, demonstrates the reliability of the results. These are applied to rank the alternatives for two criteria- Criterion I: Non-participation of students in online classes and Criterion II: Learning experience of students in online classes. According to the results of this study, the most significant alternative reveals that students experience fatigue when learning online and that prolonged screen time is quite taxing for them. The results of the various analysis techniques - RIDIT, TOPSIS and RII taken into account in the study are comparable and coherent. The results of the Spearman rank correlation study between the ranks derived from the three approaches showed a substantial positive correlation, which clearly indicates that the results are consistent across the three methods, signifying that all the findings are robust and not heavily dependent or sensitive to the specific method used.

Students miss meeting their classmates in person and prefer the physical classroom environment shared with fellow students. Knowing the issues faced by students with respect to online education, institutions can take steps to improve the online learning experience for them. This study enables educational institutions to enhance support for teachers and students by understanding OTL e vividly, and providing tailored assistance wherever required. It aims at improving academic achievement and student engagement.

Future Directions

This article is based on the dataset collected during COVID-19; it will be interesting to study the perspectives of teachers and students for offline as well as blended teaching and learning scenarios. Future work could also examine changes in perceptions in the post-pandemic era.

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Author's Contributions

Ritu Gupta and Meetu Bhatia Grover: Conceptualization, methodology, writing original draft, and final approval.

Anuradha Khattar and Priti Rai Jain: Formal analysis, software (Python), investigation, and writing review and edited.

Seema Aggarwal: Supervision and final approval of the manuscript.

Ethics

This study was conducted ethically with a data set that was already anonymized for consideration of participants' rights and well-being.

Novelty Statement

This paper focuses on online teaching learning experiences, challenges, dilemmas, and opportunities from students' perspectives. Use of multiple statistical approaches enhances its result reliability. Focus on student fatigue, a growing concern during the pandemic, particularly due to prolonged screen time and lack of interaction is an acme of this study. Data analysis and statistical methods are used to make informed choices, evaluate risks, and understand the potential outcomes of different actions. We analyze and evaluate patterns and trends that affect students' health and their academic performances during e-classes. The novelty of the work lies in the combined application of the three decision-making tools TOPSIS, RIDIT, and RII on a single dataset and validating the insights via ensemble ranking. Moreover, the current work distinguishes itself through its contextual focus on India.

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