Article

*Journal of International Students*
Volume 16, Issue 5 (2026), pp. 141-166
ISSN: 2162-3104 (Print), 2166-3750 (Online)
jistudents.org
https://doi.org/10.32674/wzmzf922

# Enhancing Global Student Success Through Data-Driven Session Design in Online Education

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***ABSTRACT:*** *Effective online learning sessions require designing sessions that address learners' engagement and achievement across diverse groups. The duration and frequency of the session affect user satisfaction and quiz results, but it is difficult to optimize both simultaneously. This paper presents a combined optimization model that uses stepwise regression, NSGA-II, and gray relational analysis (GRA) to optimize the design of a session, leveraging a publicly available e-learning dataset (more than 2,500 anonymized records). Directional relationships between session parameters and outcomes were quantified using regression models, and Pareto-optimal solutions were identified using NSGA-II, which were further assessed under three teaching-priority scenarios using GRA. The results show that a 60-minute weekly session is the optimal balance between the more satisfaction-focused designs, and that allotting 113 minutes across eight sessions is optimal for quiz performance. The explanations of the regression models (R2 = 0.20 for satisfaction and R2 = 0.11 for quiz scores) are modest, suggesting that the results should be viewed as guidance for decision-making rather than prescriptions. Despite these shortcomings, the framework emphasizes* *trade-offs between the timing and frequency of online learning and offers a data-driven, systematic approach to optimizing online learning. This research contributes to evidence-based instructional design and provides practitioners with actionable insights to enhance international online learning.*

**Keywords:** International education; Online learning optimization; Stepwise regression; NSGA-II; Gray Relational Analysis (GRA)

**Received**: Nov 21, 2025 | **Revised**: Jan 28, 2026 | **Accepted:** Feb 20, 2026

**How to Cite** (APA): Atif Saeed, M., Naeem, S.M., Imran, M., Ahmed, S., Almusharraf, N., & Azar, A.T. (2026). Enhancing global student success through data-driven session design in online education. *Journal of International Students*, 16(6), 141-166. https://doi.org/10.32674/wzmzf922

## INTRODUCTION

Online learning effectiveness depends on two key factors: the number of delivered sessions per week and the overall size of each session (Flores et al., 2025; Imran & Almusharraf, 2024a). In centrally dispersed online courses, where teaching is often provided to cohorts that are geographically and culturally diverse, the determination of the frequency of sessions (Shaw et al., 2025; Khahro et al., 2020) and duration exerts a primary influence on determining engagement (Y. Huang & Lanford, 2024), intellectual burden, and continuity of learning. Recent literature indicates that a well-organized online session, as well as a carefully planned mix of synchronous and asynchronous activities, is the key to keeping instructions clear and inclusive in the context of large-scale and cross-border learning (Barua & Lockee, 2024; Culbreth & Martin, 2025; Imran & Almusharraf, 2024b; Mansour, 2024; Zeng & Luo, 2024; Iqbal et al., 2022).

Systematic reviews and large-scale studies of online education have empirically shown that academic performance and student satisfaction are closely related to instructional characteristics, including session length, pacing, and interaction intensity, across student populations (T.-C. Huang & Tseng, 2025; Xia et al., 2024; Yu, 2025). Such findings imply the need for data-based session design interventions, which can be easily scaled in intercultural and international education environments where standardized yet adaptable instructional models are frequently needed to accommodate diverse students admitted to institutions and across geographical areas. Previous studies also emphasize that regular learning timetables and learning activities can contribute to long-term attention to online courses that cater to cohorts located worldwide (Gabler et al., 2025; Imran et al., 2024; Sahni, 2023).

The open, historical, and educational information (assessment scores, course completion, and learner satisfaction ratings) has a solid empirical foundation for enhancing decision-making in instruction at the session level. Predictive modeling and regression methods have been extensively employed to determine the most significant parameters that influence the quality of online learning and student performance results, and stepwise regression is often employed to construct parsimonious models, i.e., with the selection of relevant predictors among the larger candidate lists (Kocsis & Molnár, 2025; Mumtaz et al., 2024; Tirumanadham et al., 2024). This type of empirical model would allow the observed relationships to be translated into practical instructional parameters, such as the suggested session length and frequency of sessions per week, which would be highly valuable in large-scale online programs.

On the basis of this statistical modeling, the current manuscript suggests a hybrid optimization model that combines statistical modeling, multiobjective optimization, and multicriteria decision-making. The first step is to model the relationships between the session length and the number of sessions per week and the key performance outcomes (average quiz score and learner satisfaction). Afterward, the NSGA-II is used to examine the trade-off surface and produce Pareto-optimal session configurations that trade off rival instructional goals (Sethy et al., 2025). NSGA-II has been shown to be useful for educational scheduling and other resource-allocation problems where trade-offs among results need to be explicitly controlled. Finally, the ranked and selected balanced solutions are selected using a technique called gray relational analysis (GRA) across various prioritization scenarios; hybrid GRA/MCDM frameworks have demonstrated high performance in the context of multidimensional decision-making criteria and incomplete preference data (Harkare et al., 2024).

The given framework is implemented on the open-source online dataset with two decision variables—session duration and number of sessions per week—and three outcomes—course completion rate, learner satisfaction, and average quiz score. Three instructional scenarios are evaluated to demonstrate various priorities in pedagogy: (1) equal significance of both satisfaction and quiz performance, (2) satisfaction as a priority, and (3) quiz performance as a priority. The derived optimal session designs indicate that varying weighting strategies yield distinct evidence-based recommendations that may guide the design of online programs, including those intended for international and transnational student bodies.

The rest of the paper provides the materials and methods, results and discussion of the application of the framework to the dataset and the analysis of the three scenarios. The paper ends with implications for the design of online programs and future research directions.

## LITERATURE REVIEW

### Learning Theories Explaining Session Duration and Frequency

Online learning sessions can be designed with reference to Cognitive Load Theory (CLT) and Self-Regulated Learning (SRL) to determine the duration and number of sessions per week. According to CLT, the key to determining the effectiveness of learning lies in the capacity to manage intrinsic, extraneous, and germane cognitive loading of the limited working memory capacity of the learner. Recent changes in the fields of online and blended higher education indicate that excessively long synchronous sessions add an extra load, causing cognitive fatigue and decreasing knowledge retention, whereas appropriately divided sessions support sustained attention and schema development (Asma & Dallel, 2020; Sweller, 2024). On the other hand, too brief or too few sessions might not be able to offer adequate cognitive stimulation or sustained stimulation, which would adversely impact learning results.

SRL theory also provides details concerning how the structure of a session affects the performance of learners. SRL focuses more on how learners plan, monitor, and control their learning behaviors over time. Empirical evidence indicates that the frequency of regular sessions facilitates goal-setting, time management, and self-monitoring, especially in online settings where external structure is lacking (Kong & Lin, 2023; Selwyn, 2020). An SRL perspective would suggest that optimal session frequency is a scaffolding tool that facilitates regular engagement and reflective learning behaviors, thereby enhancing academic performance and satisfaction among learners.

Collectively, CLT and SRL justify the need for the session duration and its frequency, respectively. These complementary theories present a strong platform for analyzing the influence of session parameters on quiz scores and user satisfaction in an online learning environment.

## International Students and Differential Learning Needs

The international students make a unique subgroup with respect to online higher education given that there is a linguistic, cultural and contextual element of the international students that affects the processes of learning. According to recent studies in the area of international education, international students may find the cognitive load heavier in online contexts since they have to process second language information, analyze unfamiliar academic conventions, and have fewer options to clarify something (Department of Industrial Engineering And Management, Bandung Institute of Technology, Bandung, Indonesia et al., 2019; Imran et al., 2024; Nguyen et al., 2025, pp. 1972–2023). These aspects complicate the duration of sessions, especially long ones, which can unfairly put pressure on international students and lead to cognitive overload and diminished engagement.

Moreover, international students' reliance on structured learning environments has been well established. In addition, the dependence of international scholars on institutionalized learning settings has been extensively recorded. Research across Australia, the UK, and East Asia suggests that session frequency predictability helps international students self-regulate, alleviate anxiety, and find satisfaction through routine and predictability (Kristiana et al., 2023; Yuan et al., 2023). Conversely, disengagement and dissatisfaction are worsened by irregular schedules or poorly optimized schedules, particularly in entirely online or transnational education programs.

Even with these growing studies, the current literature primarily explores session design variables in isolation or by reference to qualitative information. Limited empirical studies exist that quantitatively describe the interactive effects of session length and frequency on performance and satisfaction, especially when optimization-based methods that support evidence-based decision-making in international education settings are used.

### Gap in Research and Contribution to the Study

Although learning theories offer powerful conceptual frameworks and international education studies emphasize differences in needs, these studies have rarely applied theory-driven modeling, multiobjective optimization, and decision-making models to one-method pipelines. The majority of empirical studies rely on regression or descriptive analysis, with no systematic investigation of trade-offs among competing outcomes, such as academic performance and learner satisfaction.

To fill this gap, the current study integrates both empirical modeling and both the NSGA-II and gray relational analysis (GRA) to determine the session configurations that would help balance cognitive efficiency and learner experience. This interconnected framework is a direct response to international education scholarship's demand for a data-driven, theoretically grounded, and responsive design of learning that serves diverse learner populations.

## METHOD

In this research paper, a hybrid approach is used to combine statistical modeling, multiobjective optimization and decision-making to establish the best design of online sessions for international students. This will be achieved by step-by-step regression to develop empirical models that can be used to relate the variables of decision, which will be session length and number of sessions per week, to the outcome measures of user satisfaction, performance on the quiz, and completion of the course. These models serve as the foundation for the optimization stage, where NSGA-II is employed to generate Pareto-optimal solutions that balance competing objectives. Subsequently, gray relational analysis (GRA) is applied to rank and select the most suitable solution under varying cases.

To understand the relationships between session design factors and student performance, stepwise regression was used to model and analyze the data. Stepwise regression models can add or drop predictor variables one at a time based on their significance. Stepwise regression produces a shorter model to reduce the likelihood of overfitting and includes only the most important predictor variables for the outcome (Y. Huang et al., 2025; Oliveira et al., 2024; Soeharto et al., 2024). In this study, the predictor variables—length of study sessions and frequency of sessions per week—are examined in relation to the three outcome variables—user satisfaction, average quiz performance, and percentage of course completion.

Pearson's correlation coefficient was calculated to examine the strength and direction of linear relationships between predictor variables and outcomes before the model outcome was developed (Han et al., 2024; Xu et al., 2024). The factor is described by Equation (1):

$$r_{xy} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \quad (1)$$

where $r_{xy}$ denotes the correlation between variables x and y, $x_i$ and $y_i$ represent individual observations, and $\bar{x}$ and $\bar{y}$ are their respective means.

Predictor variables with statistically meaningful correlation values were identified as possible candidates for inclusion in the stepwise regression model. An $\alpha = 0.15$ criterion was established for entry and removal, ensuring that only statistically meaningful predictors were retained. In this way, model interpretability was improved, and multicollinearity issues were addressed with the other predictors.

The entire procedure for applying stepwise regression in this research—including correlation analysis, variable selection, and model validation—is encapsulated in the flowchart shown in **Figure 1.**

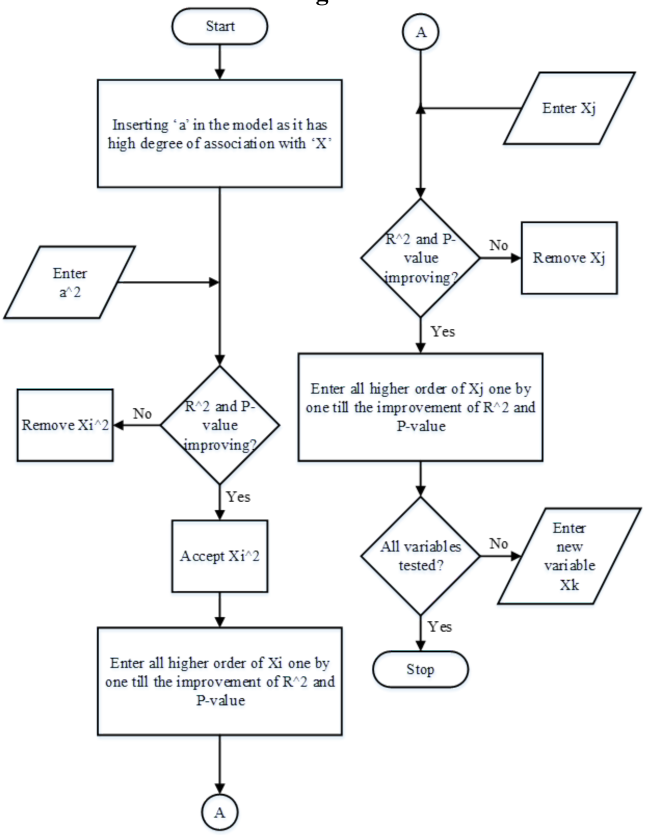


**Figure 1 Stepwise regression process flow**

The stepwise regression models in this study are not intended as high-accuracy predictive tools but rather as low-fidelity surrogate models that approximate the directional relationships between session design variables and learning outcomes. In complex behavioral systems such as online learning, outcome variance is influenced by numerous unobserved factors (e.g., learner motivation, prior knowledge, instructor quality), which are not captured in the present dataset. Consequently, modest $R^2$ values are expected and reflect data limitations rather than model misspecification. The regression models are used here to enable relative comparisons and trend-based optimization within a multiobjective framework rather than precise outcome prediction.

After the regression models are constructed, the next step is multiobjective optimization, where a balance must be made between conflicting objectives. In this case, the Nondominated Sorting Genetic Algorithm II (NSGA-II) was applied, a well-regarded evolutionary algorithm effective for addressing complex optimization problems (D. Liu, 2025; Palakonda et al., 2024; Qian & Zhang, 2025). The NSGA-II algorithm takes potential solutions and undergoes a multiple generation process, which selects, crossovers, and mutates them. The greatest strength of NSGA-II is its ability to identify many Pareto-optimal solutions, which represent the best trade-offs among conflicting goals.

In this research, NSGA-II was implemented to maximize the number of sessions and the number of sessions per week, thereby increasing user satisfaction and mean quiz scores. The algorithm produces a Pareto front of solutions, all of which depict a distinct trade-off between the two performance measures. Gray relational analysis (GRA) is then used to select the best appropriate solution.

The NSGA-II algorithm is applied within the scope of this framework, with the procedure comprising initialization, fitness evaluation, nondominance sorting, assignment of crowding distance, and next-generation selection, as shown in **Figure 2**.

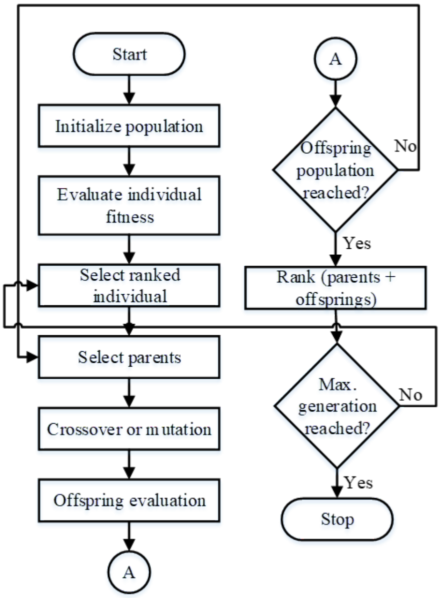


**Figure 2 NSGA-II process flow**

The effectiveness of the NSGA-II depends on proper tuning of its hyperparameters (Jdidou et al., 2025).

**Table 1** summarizes the hyperparameter values adopted in this study, which are based on commonly used settings in the literature and preliminary calibrations.

**Table 1 NSGA-II hyperparameters used in this study**

| Parameter | **Value** | **Description** |
|---|---|---|
| Population size | 100 | Number of candidate solutions in each generation |
| Number of generations | 200 | Maximum number of evolutionary cycles |
| Crossover probability | 0.9 | Probability of recombining two parent solutions |
| Mutation probability | 0.1 | Probability of mutating an offspring solution |
| Distribution index (crossover) | 20 | Controls the spread of solutions during crossover |
| Distribution index (mutation) | 20 | Controls the perturbation applied during mutation |
| Selection method | Binary tournament | Selection strategy based on nondominance and crowding distance |

These parameters were selected to balance exploration of the solution space with computational efficiency. Adjustments were validated by preliminary test runs to ensure stable convergence toward meaningful Pareto fronts.

Although the NSGA-II is used to produce a wide range of Pareto-optimal solutions, it does not specify which of the solutions should be applied in practice. To overcome this difficulty, the decision-making method that was applied was gray relational analysis (GRA). The GRA provides alternative rankings on the basis of the proximity of every solution to a desired reference, thus providing a systematic approach to determining the most balanced design of a session (M. Liu, 2024; Lu et al., 2024; Luo & Zhang, 2025).

The process begins with data normalization, which transforms performance indicators into comparable scales. Since the objectives in this study (user satisfaction and quiz score) are to be maximized, the larger-the-better normalization scheme was primarily used:

$$X_i^* = \frac{X_i(k) - \min(X_i(k))}{\max(X_i(k)) - \min(X_i(k))} \quad (2)$$

For objectives where minimization is needed, the smaller-the-better scheme may be applied as follows:

$$X_i^* = \frac{\max(X_i(k)) - X_i(k)}{\max(X_i(k)) - \min(X_i(k))} \quad (3)$$

After normalization, the deviation sequence between the normalized value and the ideal reference (which equals 1 for maximization) is calculated as follows:

$$\Delta_i = |X_0^* - X_i^*| \quad (4)$$

The gray relational coefficient**,** which quantifies the closeness of each solution to the ideal, is then obtained as follows:

$$\xi_i(k) = \frac{\Delta_{min+}\zeta\Delta_{max}}{\Delta_i(k) + \zeta\Delta_{max}} \quad (5)$$

where $\Delta_{min}$ and $\Delta_{max}$ are the minimum and maximum values of the deviation sequence, respectively, and $\zeta$ is the distinguishing coefficient, which is generally set to 0.5.

Finally, the gray relational grade (GRG) is determined as the weighted average of gray relational coefficients across all the criteria:

$$\gamma_i = \sum_{k=1}^{m} w_k \xi_i(k) \quad (6)$$

where $w_k$ denotes the relative importance assigned to each criterion. In this study, weights were defined according to three instructional priorities: equal weighting of satisfaction and quiz score, prioritizing satisfaction, and prioritizing quiz score.

The complete flow of the GRA process—covering normalization, deviation calculation, coefficient determination, and ranking—is illustrated in **Figure 3**, which shows how Pareto-optimal solutions from the NSGA-II are systematically transformed into a ranked set of alternatives, ultimately identifying the most suitable session design for international students.

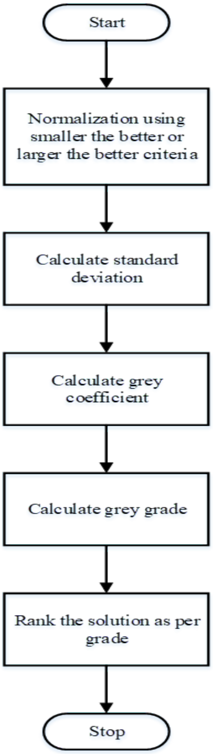


**Figure 3 GRA process flow**

In summary, the suggested methodology combines stepwise regression, NSGA-II, and GRA within a single framework for optimizing online session design. Predictive models between the independent variables (course satisfaction and quiz score) and the dependent outcome (session duration and frequency) are defined by stepwise regression. A Pareto front of optimal trade-offs is then produced with the aid of the NSGA-II, and the relative weights of the decision criteria and GRA are subsequently used to find the most suitable configuration. To be robust and flexible, three different decision cases are examined: Case 1 consists of an equal value of user satisfaction and quiz score, Case 2 presupposes the preference of user satisfaction to quiz score, and Case 3 presupposes the preference of quiz score to user satisfaction. As shown in **Figure 4**, these cases provide information on the impact of various instructional priorities on the ideal weekly sessions and duration of use. Taken together, the methodology suggests a data-driven and systematic approach to balancing the effectiveness of learning and the experience of the student, which will eventually lead international educators to design more efficient online courses.

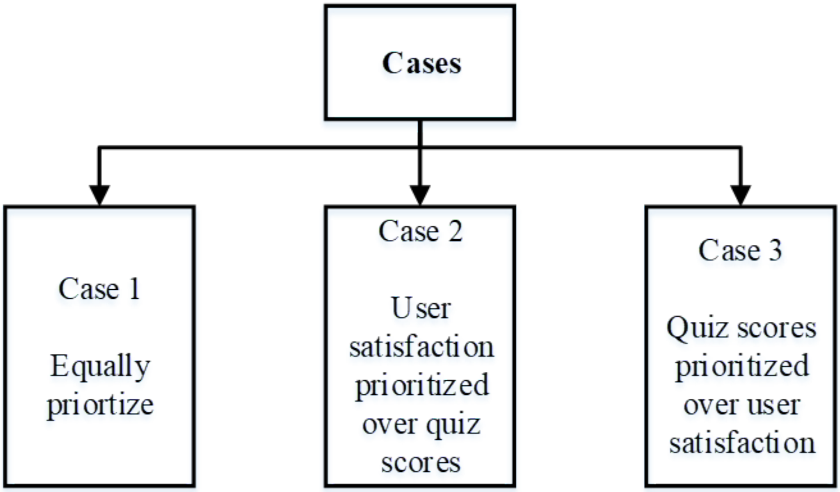


**Figure 4 Decision cases**.

## RESULTS

This section presents the results of the optimization framework, including clear indications of the empirical data and a case analysis of the optimal online session design. An anonymous dataset that is publicly available and obtained from the (*Kaggle*, n.d.) E-learning Student Dataset (Vikant Kumar) is accessible at https://www.kaggle.com/datasets/vikantkumar/e-learning-student-dataset. The dataset consists of more than 2500 learner records that were gathered in online accessible e-learning settings worldwide and with quantifiable variables that are important to instructional design, i.e., the session length, the number of sessions that the learner had every week, the average score on quizzes and the satisfaction rating of the learner. The dataset does not include any personally identifiable data, and the course titles are anonymized placeholders supplied by the dataset contributor; they are not considered analytical variables and have no impact on the quantitative outcomes. Although the dataset does not directly link learners to any nationality, it captures the patterns of use common to online learning environments distributed internationally.

**Table 2** presents selected rows to illustrate the dataset's structure, and **Figure 5** shows a visual representation of the entire dataset because it is too large. This dataset provides the empirical basis for the latter application of stepwise regression modeling, multiobjective optimization using the NSGA-II and gray relational analysis (GRA) in decision-making under the three scenarios of instructional priorities.

**Table 2 Sample anonymized records from the e-learning dataset**

| Course ID | Session Duration ($X_1$, minutes) | Sessions per Week ($X_2$) | User Satisfaction | Average Quiz Score |
|---|---|---|---|---|
| C01 | 62.76 | 4.91 | 3.09 | 74.48 |
| C02 | 62.91 | 5.22 | 2.97 | 76.70 |
| C03 | 68.35 | 4.99 | 2.95 | 72.74 |
| C04 | 60.85 | 5.11 | 2.71 | 74.64 |
| C05 | 62.71 | 4.82 | 2.98 | 73.96 |
| C06 | 60.49 | 4.90 | 3.03 | 73.51 |
| C07 | 64.09 | 5.09 | 2.82 | 74.43 |
| C08 | 62.90 | 4.98 | 3.03 | 77.08 |
| C09 | 63.06 | 5.13 | 2.71 | 75.20 |
| C10 | 65.09 | 5.06 | 2.87 | 72.87 |
| C11 | 65.81 | 4.93 | 2.95 | 74.64 |
| C12 | 56.33 | 4.66 | 3.08 | 73.66 |
| C13 | 64.49 | 4.69 | 2.99 | 74.56 |
| C14 | 64.80 | 5.40 | 3.05 | 76.56 |
| C15 | 65.12 | 4.92 | 2.94 | 74.25 |
| C16 | 63.22 | 5.39 | 3.06 | 76.41 |
| C17 | 62.77 | 4.56 | 2.97 | 75.73 |
| C18 | 57.52 | 4.52 | 3.13 | 74.10 |
| C19 | 62.30 | 4.92 | 2.95 | 76.12 |
| C20 | 63.46 | 4.79 | 2.94 | 74.50 |

***Note:*** *Course identifiers are anonymized and used solely for illustration. The original dataset provides procedurally generated course labels that do not represent actual course titles and are not used in any statistical or optimization analysis. Only quantitative instructional and performance variables are employed in this study.*

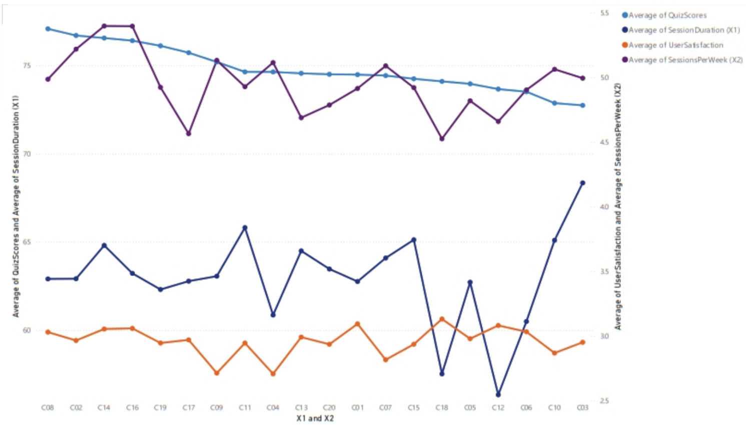

**Figure 5 Complete dataset**

To further explain the dataset and obtain a clearer picture of the relationship between the independent variables (X1: length of the session and X2: the number of sessions per week) and the responses, more light is provided in **Figure 6** and **Figure 7**. **Figure 6** indicates that the highest average quiz score of 83.36 is obtained with the 25-minute session, and the highest average satisfaction score of 3.83 is obtained with the 61-minute session. Similarly, **Figure 7** illustrates the impact of the frequency of the sessions, where one session per week gives the best average score on the quiz at 76.18 and the most intensive schedule of seven sessions per week leads to the highest user satisfaction. These facts highlight the trade-off between learning outcomes and satisfaction and emphasize the need to use optimization methods to balance these competing goals systematically and effectively in session design.

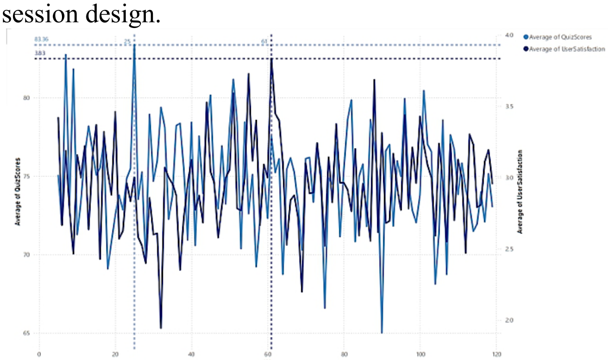

**Figure 6 Relationships between session duration (X1) and responses**

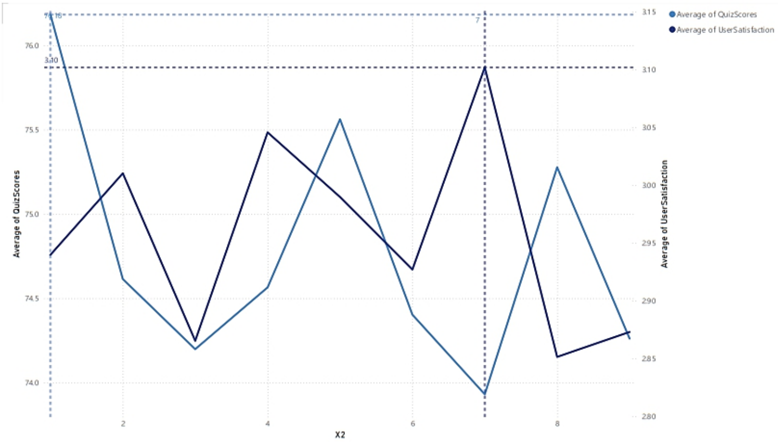


**Figure 7 Relationships between session frequency per week (X2) and responses**

The first stage of the analysis involved exploring the statistical relationships between the independent and dependent variables using Pearson's correlation coefficient (Equation (1)). The coefficients for session duration (X1) and number of sessions per week (X2) were computed from the dataset and visualized in a correlogram in **Figure 8**. The results indicate that both user satisfaction and session duration strongly positively and negatively correlated with session duration, suggesting that optimally extended sessions tend to enhance learners' perceived quality of experience, whereas shorter sessions tend to increase quiz attainment.

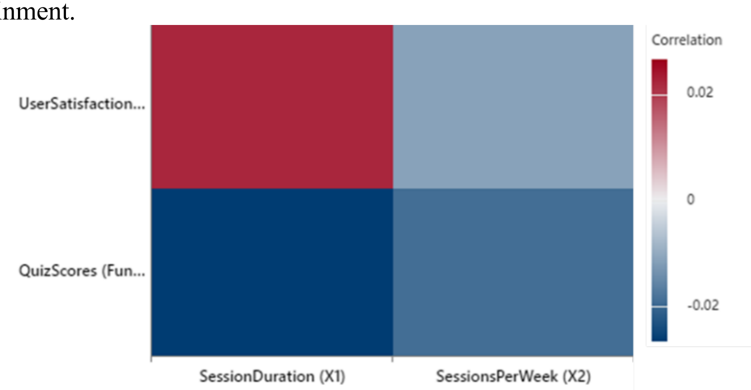


**Figure 8. Pearson's coefficient**

These insights guided the development of predictive models using stepwise regression, which sequentially included only statistically significant predictors. The resulting models for user satisfaction and quiz scores are summarized in **Table 3**, along with their corresponding $R^2$ values. The obtained coefficients of determination ($R^2$ = 0.20 for user satisfaction and $R^2$ = 0.11 for quiz scores) indicate that a substantial proportion of outcome variance remains unexplained. This is consistent with prior studies using secondary learning analytics data, which show that limited feature sets constrain explanatory power. Despite these values, the regression coefficients were statistically significant and directionally consistent, supporting their use as empirical response surfaces for exploratory optimization rather than deterministic forecasting. The optimization results should therefore be interpreted as identifying plausible trade-off regions rather than exact optimal solutions.

**Table 3 Mathematical models**

| Response | Model | R-square value |
|---|---|---|
| user satisfaction | 3.121 - 0.00204 X1 - 0.0451 X2 + 0.000607 X1*X2 | 0.20 |
| quiz scores | 76.020 - 0.01131 X1 - 0.105 X2 | 0.11 |

On the basis of the mathematical models developed, NSGA-II was used to maximize the user satisfaction and quiz scores both together after the session length and session frequency were maximized. The algorithm was effective in searching through the solution space and produced a rich array of trade-off solutions, which represent the internal conflict between academic performance and maximizing satisfaction. The Pareto-optimal front that developed is represented in **Figure 9**, which shows the distribution of the nondominated solutions and indicates the balance between the two objectives. It is possible to visualize the entire set of optimal solutions in **Figure 10**. As shown by the analysis, the number of sessions per week and the duration of the sessions demonstrate an inverse correlation; i.e., the longer the sessions are in general, the fewer sessions they have weekly and vice versa. This trade-off highlights the need to strike a balance between long, intensive learning and short, but more frequent interactions.

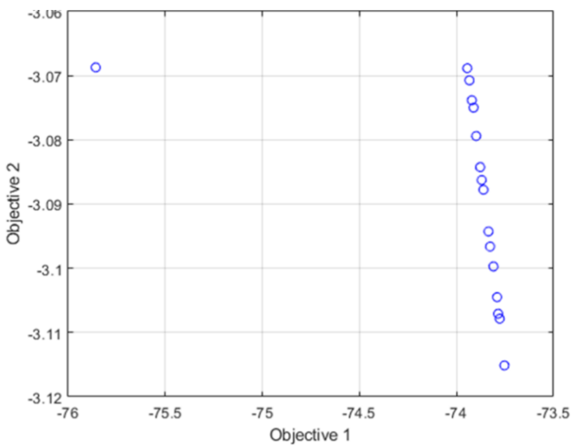


**Figure 9 Pareto plot**

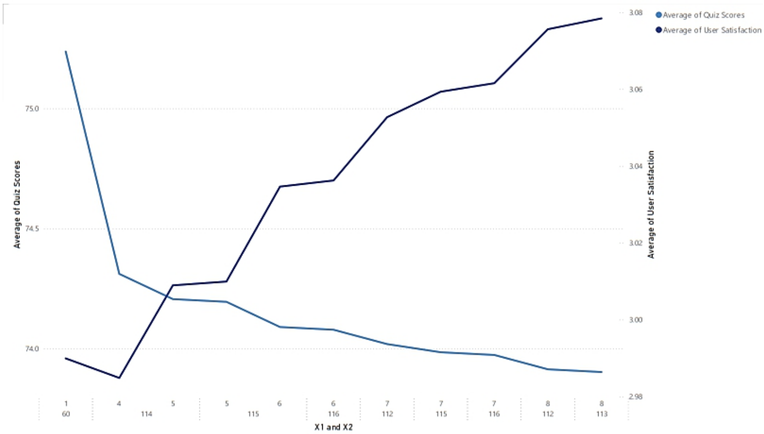


**Figure 10 Optimal solution set**

To provide more information, the set of solutions of optimal solutions with attached trade-offs can be summarized in **Table 4**. Both solutions offer a viable alternative to the two outcomes, as each provides a different ratio of session time to weekly session frequency. Indicatively, some solutions, in turn, prefer the user to be more satisfied with satisfactory quiz performance, whereas they sacrifice some of the satisfaction to obtain better quiz scores. This Pareto front forms the basis for further decision-making, where the relative significance of the criteria is considered by using weight, and the ultimate rankings are made by use of GRA.

**Table 4 Optimal solution set**

| Session Duration (X1) | SessionsPer Week (X2) | Quiz Scores | User Satisfaction |
|---|---|---|---|
| 60.00 | 1.00 | 75.24 | 2.99 |
| 112.00 | 8.00 | 73.91 | 3.08 |
| 116.00 | 6.00 | 74.08 | 3.04 |
| 116.00 | 7.00 | 73.97 | 3.06 |
| 114.00 | 5.00 | 74.21 | 3.01 |
| 115.00 | 7.00 | 73.98 | 3.06 |
| 115.00 | 5.00 | 74.19 | 3.01 |
| 115.00 | 6.00 | 74.09 | 3.03 |
| 115.00 | 7.00 | 73.98 | 3.06 |
| 112.00 | 7.00 | 74.02 | 3.05 |
| 114.00 | 4.00 | 74.31 | 2.98 |
| 113.00 | 8.00 | 73.90 | 3.08 |

Gray relational analysis (GRA) was used to determine the solution set providing the most appropriate session design among the solutions generated by NSGA-II. Given that both the results, user satisfaction, and quiz scores, were maximization goals, a first normalization of the solution set was performed with the criterion, larger-the-better, of Equation (2). This normalization resulted in all data falling within the range 0 to 1, with higher values indicating better performance.

**Table 5 Gray relational coefficients of the optimal solutions**

| | | | | **Normalization** | | **Deviation Sequence** | | **Gray Relational Coefficient** | |
|---|---|---|---|---|---|---|---|---|---|
| Session Duration (X1) | Sessions Per Week (X2) | Quiz Scores | User Satisfaction | Quiz Scores | User Satisfaction | Quiz Scores | User Satisfaction | Quiz Scores | User Satisfaction |
| 60.000 | 1.000 | 75.23 | 2.990 | 1.000 | 0.054 | 0.000 | 0.946 | 1.000 | 0.346 |
| 112.000 | 8.000 | 73.91 | 3.076 | 0.008 | 0.970 | 0.992 | 0.030 | 0.335 | 0.943 |
| 116.000 | 6.000 | 74.07 | 3.036 | 0.132 | 0.549 | 0.868 | 0.451 | 0.365 | 0.526 |
| 116.000 | 7.000 | 73.97 | 3.062 | 0.053 | 0.820 | 0.947 | 0.180 | 0.346 | 0.735 |
| 114.000 | 5.000 | 74.20 | 3.009 | 0.228 | 0.258 | 0.772 | 0.742 | 0.393 | 0.402 |
| 115.000 | 7.000 | 73.98 | 3.059 | 0.062 | 0.796 | 0.938 | 0.204 | 0.348 | 0.710 |
| 115.000 | 5.000 | 74.19 | 3.010 | 0.219 | 0.268 | 0.781 | 0.732 | 0.390 | 0.406 |
| 115.000 | 6.000 | 74.08 | 3.035 | 0.140 | 0.532 | 0.860 | 0.468 | 0.368 | 0.517 |
| 115.000 | 7.000 | 73.98 | 3.059 | 0.062 | 0.796 | 0.938 | 0.204 | 0.348 | 0.710 |
| 112.000 | 7.000 | 74.01 | 3.053 | 0.087 | 0.725 | 0.913 | 0.275 | 0.354 | 0.645 |
| 114.000 | 4.000 | 74.31 | 2.985 | 0.306 | 0.000 | 0.694 | 1.000 | 0.419 | 0.333 |
| 113.000 | 8.000 | 73.90 | 3.078 | 0.000 | 1.000 | 1.000 | 0.000 | 0.333 | 1.000 |
| | Max | 75.24 | 3.08 | | | | | | |
| | Min | 73.90 | 2.98 | | | | | | |

The deviation sequences were computed after normalization to determine the difference between each solution and the ideal reference value. Afterward, the gray relational coefficients were calculated with the help of Equations (4) and (5), which describe the proximity of each solution to the optimal reference point. **Table 5** summarizes the full range of deviations and relational coefficients for the solutions. Such values serve as the foundation for calculating the grade-related gray (GRG) in the subsequent step, which ranks the solutions and provides unambiguous advice on the best combination of session time and weekly frequency for various teaching priorities.

The last step of decision-making was the calculation of the gray relational grades (GRGs) of each solution with the help of the equations (6) The calculation was carried out under three different conditions that represented three different instructional priorities. In Case 1, user satisfaction and quiz scores were given the same weight of 50% each to indicate an equal focus on the two results. In Case 2, the ratio was 75% user satisfaction and 25% quiz scores, with a preference for learners' experience and engagement. In Case 3, on the other hand, the weight of quiz scores was 75%, and the weight of satisfaction was 25%, indicating that academic achievement was prioritized.

**Table 6** shows the resulting GRG values and rankings. An evaluation of the prioritized solutions reveals that in Cases 1 and 2, the most desirable trade-off is achieved at 60 minutes once a week; thus, a session design is effective at balancing both engagement and performance, although it is skewed toward higher satisfaction in Case 2.

**Table 6 Ranking of the optimal solution**

| Session Duration (X1) | Sessions Per Week (X2) | Case 1 | | Case 2 | | Case 3 | |
|---|---|---|---|---|---|---|---|
| | | GRG | Ranking | GRG | Ranking | GRG | Ranking |
| 60.00 | 1.00 | 0.672935332 | 1 | 0.509402998 | 7 | 0.836467666 | 1 |
| 112.00 | 8.00 | 0.639228936 | 3 | 0.79122966 | 2 | 0.487228211 | 3 |
| 116.00 | 6.00 | 0.445701353 | 8 | 0.485810975 | 8 | 0.405591731 | 8 |
| 116.00 | 7.00 | 0.540331837 | 4 | 0.637695611 | 3 | 0.442968063 | 4 |
| 114.00 | 5.00 | 0.397687071 | 11 | 0.400054552 | 11 | 0.395319591 | 11 |
| 115.00 | 7.00 | 0.529023071 | 5 | 0.619714159 | 4 | 0.438331982 | 5 |
| 115.00 | 5.00 | 0.398123833 | 10 | 0.402009752 | 10 | 0.394237913 | 12 |
| 115.00 | 6.00 | 0.442189107 | 9 | 0.479403411 | 9 | 0.404974802 | 9 |
| 115.00 | 7.00 | 0.529023071 | 5 | 0.619714159 | 4 | 0.438331982 | 5 |
| 112.00 | 7.00 | 0.499677938 | 7 | 0.572568248 | 6 | 0.426787628 | 7 |
| 114.00 | 4.00 | 0.376093487 | 12 | 0.35471341 | 12 | 0.397473563 | 10 |
| 113.00 | 8.00 | 0.666666667 | 2 | 0.833333333 | 1 | 0.5 | 2 |

In Case 3, the optimal design is changed to 113 minutes per week in 8 shorter sessions, indicating the advantage of frequent, short engagements in maximizing quiz performance. The results point to the significant role of relative prioritization of educational goals in shaping the design of online learning sessions, underscoring the usefulness of the suggested hybrid structure for personalizing online learning for international students.The findings indicate that the hybrid optimization model is efficient at developing the best online session designs for international students. The stepwise regression models helped to consider the statistical associations between the parameters of the session and the learning results, whereas NSGA-II managed to determine the trade-offs between user satisfaction and the quiz results. Follow-up GRA-based decision-making presented explicit rankings of three case instructional priorities, which indicate that a 60-minute single session every week has the best rank when satisfaction is the same or highly ranked (Cases 1 and 2), and a 113-minute eight-minute session is the best for supporting quiz performance (Case 3). Further dataset analyses also indicated that shorter sessions yield better quiz results, whereas longer or more frequent sessions yield a better experience of student satisfaction, which explains why the interaction between the instructional design and the experience of a student is rather subtle. Taken together, these results confirm that the suggested methodology is an effective support tool for balancing engagement and performance in online international education.

These observations highlight the inherent trade-off between performance and satisfaction and emphasize a combination of optimization processes to strike a balance between the two in session design. These recommendations may be adopted by the institutions by organizing sessions on the basis of the intended learning outcome: in the case of satisfaction-oriented outcomes, single and longer sessions may be good, but in the case of performance-oriented ones, several, shorter sessions spread throughout the week are encouraged. This would be a viable model in terms of scheduling online courses using historical data in terms of engagement and performance, and can be applied to any group of learners, including those in different global settings.

## CONCLUSION

This paper describes a hybridization of optimization methods, namely, stepwise regression, NSGA-II and gray relational analysis (GRA), to identify feasible online session designs among international students. The framework was used to model the relationships among session duration, session frequency, user satisfaction and quiz scores using a publicly available dataset that contained more than 2,500 anonymized entries. The findings show that the design of a session determines the outcomes and experiences of a learner: user satisfaction as a priority parameter leads to the introduction of a single 60-minute weekly session as one of the favorable designs, but to achieve the highest results in quiz performance, allocating 113 minutes in eight sessions is better.

Although the regression models showed weak explanatory power (R2 = 0.20 for satisfaction and R2 = 0.11 for quiz scores), they reflected directional dynamics that were adequate for multiobjective optimization of an exploratory nature. This paper highlights the role of information in informed decision-making in online learning and offers a systematic way of harmonizing conflicting teaching goals.

Such limitations include the lack of demographic and contextual variables, which prevent the specific identification of international learners, and the moderate R2 values, which suggest that optimization is advisory rather than decision-making policy. Future studies may add richer learner-level cues, test the framework across a variety of online settings, and investigate adaptive and real-time teaching models that leverage AI and sensor-based learning analytics to further improve engagement and achievement in the global classroom.

**Acknowledgment**

*This paper is derived from a research grant funded by the Research, Development, and Innovation Authority (RDIA), Kingdom of Saudi Arabia, with grant number 13382-psu-2023-PSNU-R-3-1-EI-. The authors would like to acknowledge Prince Sultan University, Riyadh, Saudi Arabia, for their support of the APC of this publication. This research is supported by the Automated Systems and Computing Lab (ASCL), Prince Sultan University, Riyadh, Saudi Arabia.*
*In the preparation of this manuscript, we did not utilize artificial intelligence (AI) tools for content creation*

**Funding Statement**
*This study is supported by Prince Sultan University.*

**Competing interests**
*The authors declare that they have no competing interests.*

**Data Availability Statement**
*The dataset used in this study is publicly available at Kaggle:*
*https://www.kaggle.com/datasets/vikantkumar/e-learning-student-dataset.*

**Ethics Statement**
*This study uses fully anonymized, publicly available secondary data and does not involve human subject interaction; therefore, ethical approval was not needed.*

## REFERENCES

Asma, H., & Dallel, S. (2020). Cognitive load theory and its relation to instructional design: perspectives of some Algerian University teachers of English. *Arab World English Journal*, *11*(4), 110–127. https://doi.org/10.24093/awej/vol11no4.8

Barua, L., & Lockee, B. B. (2024). A review of strategies to incorporate flexibility in higher education course designs. *Discover Education*, *3*(1), 127. https://doi.org/10.1007/s44217-024-00213-8

Culbreth, D., & Martin, F. (2025). Exploring the role of synchrony in asynchronous, synchronous, and quasisynchronous online learner engagement. *Educational Technology Research and Development*. https://doi.org/10.1007/s11423-025-10504-y

Bandung, Indonesia, Moses Okuni, I., Widyanti, A., & Department of Industrial Engineering And Management, Bandung Institute of Technology, Bandung, Indonesia. (2019). International students' cognitive load in learning through a foreign language of instruction: a case of learning using Bahasa - Indonesia. *PEOPLE: International Journal of Social Sciences*, *4*(3), 1503–1532. https://doi.org/10.20319/pijss.2019.43.15031532

Flores, V. A., Silveira, S. L., Marquez, D. X., Kinnett-Hopkins, D., Miravalle, A., Sierra-Morales, F., Hernández-Peraza, Z., & Motl, R. W. (2025). Rationale for a 4-month, parallel-group, randomized controlled trial to assess the Feasibility and Efficacy of a Remotely delivered exercise training intervention for Hispanics/Latinos with Multiple Sclerosis (FERLA MS). *Pilot and Feasibility Studies*, *11*(1), 62. https://doi.org/10.1186/s40814-025-01641-5

Gabler, C., Seebacher, T., & Seebacher, U. (2025). Case study predictive communication intelligence for educational institutions. In U. Seebacher, J. Forthmann, & T. Mickeleit (Eds.), *Mastering CommTech* (pp. 329–366). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-90302-1_14

Han, H., Zeeshan, Z., Talpur, B. A., Sadiq, T., Bhatti, U. A., Awwad, E. M., Al-Razgan, M., & Ghadi, Y. Y. (2024). Studying long term relationship between carbon Emissions, Soil, and climate Change: Insights from a global Earth modeling Framework. *International Journal of Applied Earth Observation and Geoinformation*, *130*, 103902. https://doi.org/10.1016/j.jag.2024.103902

Harkare, V., Mangrulkar, R., Thorat, O., & Jain, S. R. (2024). Evolutionary Approaches for Multiobjective Optimization and Pareto-Optimal Solution Selection in Data Analytics. In N. Dey (Ed.), *Applied Multiobjective Optimization* (pp. 67–94). Springer Nature Singapore. https://doi.org/10.1007/978-981-97-0353-1_4

Huang, T.-C., & Tseng, H.-P. (2025). Extended Reality in Applied Sciences Education: A Systematic Review. *Applied Sciences*, *15*(7), 4038. https://doi.org/10.3390/app15074038

Huang, Y., Cho, M., Chakraborty, S., & Dey, T. (2025). Variable Selection for Prediction in Clinical Research. *WIREs Computational Statistics*, *17*(2). https://doi.org/10.1002/wics.70030

Huang, Y., & Lanford, M. (2024). Framing the barriers to collaborative online international learning implementation: The impact of political, infrastructural, temporal, and experiential factors. *Globalization, Societies and Education*, 1–13. https://doi.org/10.1080/14767724.2024.2302821

Iqbal, S. A., Ashiq, M., Rehman, S. U., Rashid, S., & Tayyab, N. (2022). Students' perceptions and experiences of online education in Pakistani universities and higher education institutes during COVID-19. *Education Sciences*, *12*(3), 166.

Imran, M., & Almusharraf, N. (2024a). Digital Learning Demand and Applicability of Quality 4.0 for Future Education: A Systematic Review.

*International Journal of Engineering Pedagogy (iJEP)*, *14*(4), 38–53. https://doi.org/10.3991/ijep.v14i4.48847

Imran, M., & Almusharraf, N. (2024b). Google Gemini as a next generation AI educational tool: A review of emerging educational technology. *Smart Learning Environments*, *11*(1), 22. https://doi.org/10.1186/s40561-024-00310-z

Imran, M., Almusharraf, N., Ahmed, S., & Mansoor, M. I. (2024). Personalization of E-Learning: Future Trends, Opportunities, and Challenges. *International Journal of Interactive Mobile Technologies (iJIM)*, *18*(10), 4–18. https://doi.org/10.3991/ijim.v18i10.47053

Jdidou, Y., Aammou, S., Er-radi, H., & Aarab, I. (2025). Gradient-enhanced evolutionary multiobjective optimization (GEEMOO): Balancing relevance, learning outcomes, and diversity in educational recommendation systems. *Intelligent Systems with Applications*, *27*, 200568. https://doi.org/10.1016/j.iswa.2025.200568

*Kaggle: Your Machine Learning and Data Science Community*. (n.d.). Retrieved 15 January 2026, from https://www.kaggle.com/

Khahro, S. H., Yusof, A., Talpur, M. A. A., Khoso, A. R., & Ali, F. H. (2020). Are we doing enough for students with disabilities: A case of online education during Covid-19 pandemic?. Elementary Education Online, 19(3), 2180-2183.

Kocsis, Á., & Molnár, G. (2025). Factors influencing academic performance and dropout rates in higher education. *Oxford Review of Education*, *51*(3), 414–432. https://doi.org/10.1080/03054985.2024.2316616

Kong, S.-C., & Lin, T. (2023). Developing self-regulated learning as a pedagogy in higher education: An institutional survey and case study in Hong Kong. *Heliyon*, *9*(11), e22115. https://doi.org/10.1016/j.heliyon.2023.e22115

Kristiana, I. F., Prihatsanti, U., Simanjuntak, E., & Widayanti, C. G. (2023). Online Student Engagement: The Overview of HE in Indonesia. *The International Review of Research in Open and Distributed Learning*, *24*(3), 34–53. https://doi.org/10.19173/irrodl.v24i3.7125

Liu, D. (2025). Research on Balanced Allocation of English Educational Resources Based on Multiobjective Optimization and NSGA-II. *Journal of Information & Knowledge Management*, *24*(02), 2550015. https://doi.org/10.1142/S0219649225500157

Liu, M. (2024). A combined exponential TODIM-GRA framework for multiple-attribute group decision-making under 2-tuple linguistic Pythagorean fuzzy sets and applications to art teaching quality evaluation in higher education institutions. *Soft Computing*, *28*(17–18), 10317–10330. https://doi.org/10.1007/s00500-024-09786-w

Lu, R., Gao, G., & Xiang, Y. (2024). Extended ExpTODIM Framework Based on Improved GRA Approach for Comprehensive Quality Evaluation of Physical Education Institutions Under Hesitant Triangular Fuzzy Sets. *IEEE Access*, *12*, 117581–117594. https://doi.org/10.1109/ACCESS.2024.3447355

Luo, Z., & Zhang, X. (2025). AI in education risk assessment mechanism analysis. *Applied Economics*, *57*(16), 1949–1961. https://doi.org/10.1080/00036846.2024.2321835

Mansour, N. (2024). Students' and facilitators' experiences with synchronous and asynchronous online dialogic discussions and e-facilitation in understanding the Nature of Science. *Education and Information Technologies*. https://doi.org/10.1007/s10639-024-12473-w

Mumtaz, F., Jehangiri, A. I., Ishaq, W., Ahmad, Z., Alramli, O. I., Ala'anzy, M. A., & Ghoniem, R. M. (2024). Quality of interaction-based predictive model for support of online learning in pandemic situations. *Knowledge and Information Systems*, *66*(3), 1777–1805. https://doi.org/10.1007/s10115-023-01995-3

Nguyen, H. T. L., Tran, L. T., Thao Luu, A. P., Luong, D. H., & Pham, H. H. (2025). Trends and Patterns of Research on Transnational Education: A Bibliometric Analysis with Scopus Data, 1972–2023. *Journal of Studies in International Education*, 10283153251375406. https://doi.org/10.1177/10283153251375406

Oliveira, A. S. B., Fernandes, J. V. A., Figueiredo, V. L. F. A., Leonel, L. C. P. C., Bauman, M. M. J., Link, M. J., & Peris-Celda, M. (2024). 3D Models as a Source for Neuroanatomy Education: A Stepwise White Matter Dissection Using 3D Images and Photogrammetry Scans. *Brain Topography*, *37*(6), 947–960. https://doi.org/10.1007/s10548-024-01058-y

Palakonda, V., Kang, J.-M., & Jung, H. (2024). Clustering-Aided Grid-Based One-to-One Selection-Driven Evolutionary Algorithm for Multi/Many-Objective Optimization. *IEEE Access*, *12*, 120612–120623. https://doi.org/10.1109/ACCESS.2024.3398415

Qian, F., & Zhang, L. (2025). Research on the Application System of Multi-Objective Optimization Algorithm in the Allocation of Educational Resources in Colleges and Universities. *2025 Asia-Europe Conference on Cybersecurity, Internet of Things and Soft Computing (CITSC)*, 972–976. https://doi.org/10.1109/CITSC64390.2025.00181

Sahni, J. (2023). Is learning analytics the future of online education?: assessing student engagement and academic performance in the online learning environment. International Journal of Emerging Technologies in Learning (iJET), 18(2), 33-49.

Selwyn, N. (2020). Reimagining 'Learning Analytics' … a case for starting again? *The internet and Higher Education*, *46*, 100745. https://doi.org/10.1016/j.iheduc.2020.100745

Sethy, B. P., Gupta, P., Chandra, A., Sethi, K. C., Behera, A. P., & Sharma, K. (2025). Optimizing construction time, cost, and quality: A hybrid AHP-NSGA-III model for enhanced multiobjective decision making. *Asian Journal of Civil Engineering*, *26*(3), 1043–1057. https://doi.org/10.1007/s42107-024-01232-4

Shaw, L., Turick, M., & Kiegaldie, D. (2025). Collaborative online international learning in health professions education: A 10-year scoping review. *Nurse Education Today*, *148*, 106602. https://doi.org/10.1016/j.nedt.2025.106602

Soeharto, S., Subasi Singh, S., & Afriyanti, F. (2024). Associations between attitudes toward inclusive education and teaching for creativity for Indonesian preservice teachers. *Thinking Skills and Creativity*, *51*, 101469. https://doi.org/10.1016/j.tsc.2024.101469

Sweller, J. (2024). Cognitive load theory and individual differences. *Learning and Individual Differences*, *110*, 102423. https://doi.org/10.1016/j.lindif.2024.102423

Tirumanadham, N. S. K. M. K., S, T., & M, S. (2024). Improving predictive performance in e-learning through hybrid 2-tier feature selection and hyper parameter-optimized 3-tier ensemble modeling. *International Journal of Information Technology*, *16*(8), 5429–5456. https://doi.org/10.1007/s41870-024-02038-y

Xia, Y., Shin, S.-Y., & Shin, K.-S. (2024). Designing personalized learning paths for foreign language acquisition using big data: Theoretical and empirical analysis. *Applied Sciences*, *14*(20), 9506. https://doi.org/10.3390/app14209506

Xu, J., Chen, Q., Xue, B., & Zhang, M. (2024). A new concordance correlation coefficient based fitness function for genetic programming for symbolic regression. *2024 IEEE Congress on Evolutionary Computation (CEC)*, 01–08. https://doi.org/10.1109/CEC60901.2024.10611932

Yu, J. H. (2025). Integrating actionable analytics into learning design for MOOCs: A design-based research. *Journal of Computing in Higher Education*, *37*(3), 993–1031. https://doi.org/10.1007/s12528-024-09413-5

Yuan, X., Yang, Y., & McGill, C. (2023). Impact of Academic Advising Activities on International Students' Sense of Belonging. *Journal of International Students*, *14*(3). https://doi.org/10.32674/jis.v14i3.5227

Zeng, H., & Luo, J. (2024). Effectiveness of synchronous and asynchronous online learning: A meta-analysis. *Interactive Learning Environments*, *32*(8), 4297–4313. https://doi.org/10.1080/10494820.2023.2197953

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