

RESEARCH ARTICLE

Evaluating undergraduate students' engagement in Blended Learning: An integrated Entropy Weight Method (EWM) and DEMATEL approach

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Abstract - Blended learning has become a new digital paradigm that has shifted away from the conventional teaching approach, especially after the Covid-19 pandemic. In higher education, the integration of blended learning into a course requires high engagement from both stakeholders, particularly the students as the main audience. However, very few studies to date have applied a systematic and objective method to determine which factors would engage students during blended learning sessions, and how these factors influence one another. To address this gap, this study introduces a combined approach that integrates the Entropy Weight Method (EWM) with the Decision-Making Trial and Evaluation Laboratory (DEMATEL) technique to highlight the most predominant engagement factor. EWM is applied to assign objective weights to each criterion based on the variability observed in the data, while DEMATEL is used to uncover cause-and-effect relationships among the criteria. Eight engagement criteria were selected based on previous studies, and undergraduate students at Universiti Teknologi MARA (UiTM), Negeri Sembilan Branch, Seremban Campus were chosen as the respondents. The results show that Interaction Quality emerged as the most influential factor in shaping students' engagement, followed by Emotional Engagement and Learning Satisfaction. Meanwhile, Technology Support and Instructional Design were identified as the main driving forces that influence the other engagement factors within the system. These findings provide useful guidance for educators and policymakers in identifying which engagement factors should be prioritised when designing strategies to enhance student involvement in blended learning environments.

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1. Introduction

Changes in how knowledge is delivered in education, particularly through the use of digital technology, have been practised for quite some time. However, since the Covid-19 pandemic, the way knowledge is conveyed has shifted dramatically, where teaching and learning had to continue through a borderless digital world during urgent circumstances. The current global situation has further reinforced this shift, with the ongoing conflict in the Middle East disrupting global oil supplies and Malaysia recently directing several states to implement work-from-home arrangements, including in higher education institutions [1]. Given these circumstances, blended learning has come up as one of the practical solutions in higher education. It combines conventional in-class teaching with digital learning components, providing students with greater flexibility and improved access to learning resources [2, 3]. This shift also reflects the readiness of higher education institutions to adapt to the Education 5.0 context, where blended learning serves as an integrated approach that connects technology with innovative teaching and learning methods [4]. As this mode of teaching continues to expand, identifying the elements that contribute to a meaningful blended learning experience has become an essential area of research.

One of the key elements that determines whether blended learning succeeds or fails is student engagement, which refers to how students involve themselves behaviourally, cognitively, and emotionally throughout the learning process [5]. Highly engaged students tend to manage their learning better, persist through tasks, and achieve stronger academic outcomes [6, 7]. However, sustaining engagement is not always easy, as students still struggle with issues such as poorly designed lessons, weak interaction with instructors and peers, and limited motivation, particularly in online settings [2]. To evaluate multiple interrelated engagement factors, Multi-Criteria Decision-Making (MCDM) approaches have been widely applied in educational research [8]. MCDM provides a structured method for evaluating complex problems that involve several interrelated criteria, making it particularly suitable for studies on student engagement where multiple factors interact simultaneously. Entropy Weight Method (EWM) and Decision-Making Trial and Evaluation Laboratory (DEMATEL) are among the various MCDM techniques. EWM determines criterion weights by calculating information entropy, where lower entropy (assuming reliable information sources) indicates greater information content and higher relative importance within the evaluation context [9]. On the other hand, DEMATEL is a well-established causal analysis technique that identifies the key factors in a decision-making problem and examines the causal relationships and interdependencies among them [10]. Although both methods have been widely applied independently, their integration enables researchers to determine the relative importance of factors while simultaneously capturing the causal relationships among them. Recognizing that EWM ignores interdependencies among factors whereas DEMATEL relies heavily on subjective judgments, Jiang et al. [11] proposed an integrated EWM–DEMATEL approach to overcome these limitations.

However, their study was conducted in a different application domain rather than the educational context. To date, no studies have applied this integrated approach to identify the most predominant student engagement factors in Malaysian higher education institutions.

To address this gap, this study proposes an integrated EWM–DEMATEL framework to identify and evaluate key factors influencing students' engagement in blended learning at Universiti Teknologi MARA (UiTM), Negeri Sembilan Branch, Seremban Campus. The study has two main objectives: (1) to identify the key factors that affect students' engagement in blended learning, and (2) to determine the relative importance of these factors using EWM while exploring their causal relationships using DEMATEL. By combining objective weighting with causal analysis, this study offers a more systematic way of evaluating student engagement and provides practical insights for educators and decision-makers in higher education.

2. Literature Review

2.1 Blended Learning in Higher Education

Blended learning is generally defined as the deliberate integration of face-to-face classroom instruction with online learning activities, aimed at enhancing flexibility, accessibility, and learning quality [2, 3]. Rather than replacing traditional teaching, this approach makes use of digital technologies to support learning activities before, during, and after face-to-face sessions, allowing institutions to cater to diverse learner needs without compromising instructional quality [12, 13]. The structural complexity of blended learning environments arises from the simultaneous interaction of multiple elements, including instructional design, technological infrastructure, assessment systems, and learner characteristics, all of which must be well-coordinated to achieve coherence between online and offline learning experiences [14]. Empirical research consistently highlights that the misalignment of these components can negatively affect learning outcomes and diminish student engagement, underscoring the need for a multidimensional evaluation approach rather than relying on a single performance measure [12, 15, 16].

2.2 Students Engagement in Blended Learning

Student engagement is widely recognised as a critical determinant of learning effectiveness in higher education, particularly in blended learning environments [7]. It refers to the extent to which students are actively involved in the learning process, the mental effort they invest in course materials, and the quality of their emotional connection to the learning environment [5]. While blended learning offers opportunities to enhance engagement through flexible access and personalised guidance, inadequate integration of online and offline components can result in fragmented learning experiences and reduced engagement [6, 12]. Student engagement is therefore recognised as a multidimensional construct that is commonly conceptualised across three primary dimensions [7, 16]:

- **Behavioural Engagement** refers to students' observable participation in learning activities, such as attendance, task completion, and active use of digital learning platforms [3, 12].
- **Cognitive Engagement** involves the mental effort students invest in comprehending learning materials and regulating their own learning processes [13, 17].
- **Emotional Engagement** encompasses students' affective responses to the learning environment, including interest, motivation, and a sense of belonging [5, 18]

Beyond these three dimensions, the existing literature consistently identifies five additional criteria as central to evaluating student engagement in blended learning:

- **Interaction Quality** — the effectiveness of communication and collaboration between students, instructors, and learning systems [7, 18].
- **Instructional Design** — the organisation and alignment of online and face-to-face activities with learning objectives [2, 14].
- **Technology Support** — the availability, reliability, and usability of digital platforms [2, 3].
- **Assessment and Feedback** — the mechanisms through which learning progress is monitored and supported [14, 19].
- **Learning Satisfaction** — students' overall evaluation of their blended learning experience [6, 7].

Table 1 highlights the criteria used by selected studies to identify students' engagement in blended learning environments. As shown, Behavioral Engagement appears across all nine studies, making it the most consistently adopted criterion. Interaction Quality and Instructional Design are similarly well-represented, appearing in eight and seven studies respectively, while Cognitive Engagement and Technology Support are each cited in seven studies. Emotional Engagement, Assessment and Feedback, and Learning Satisfaction each appear in five studies. Notably, Chu [12], Xue [13], and Huang and Yu [18] incorporate all eight criteria. Together, these criteria form the basis for the evaluation framework adopted in our study.

Table 1. Summary of Previous Studies on Criteria Influencing Students' Engagement in Blended Learning

Authors (year)	BE	CE	EE	IQ	ID	TS	ASF	LS
Chu [12]	x	x	x	x	x	x	x	x
Xue [13]	x	x	x	x	x	x	x	x
Huang & Yu [14]	x	x	x	x	x	x	x	x

Kustiyahningsih et al. [14]	x	x		x	x		x	
Yakaiah & Rani [19]	x			x	x	x	x	
Aldowah [7]	x	x	x	x		x		x
Zhang et al. [15]	x	x		x	x		x	
Nguyen et al. [16]	x	x	x		x	x		x
This study	x	x	x	x	x	x	x	x

Note: BE = Behavioral Engagement, CE = Cognitive Engagement, EE = Emotional Engagement, IQ = Interaction Quality, ID = Instructional Design, TS = Technology Support, ASF = Assessment and Feedback, and LS = Learning Satisfaction.

2.3 MCDM in Blended Learning Research

MCDM methods provide a structured approach to evaluating complex problems involving multiple interrelated criteria and have been increasingly applied in educational research to assess the quality and effectiveness of blended learning environments [16]. Among these, hybrid MCDM approaches have gained growing attention for evaluating blended learning due to their ability to integrate the strengths of different decision-making techniques [13]. For this study, two MCDM methods were used, namely the EWM and DEMATEL to determine the drivers for students of UiTM Negeri Sembilan, Seremban Campus engagement in blended learning.

2.3.1 EWM for Objective Criteria Weighting

EWM is an objective weighting technique grounded in information entropy theory that determines the relative importance of evaluation criteria based on the degree of informational variability in the data [20]. Unlike subjective approaches that rely on expert judgement, EWM derives weights directly from data distributions, thereby minimising individual bias in the evaluation process [11]. This makes EWM particularly suitable for assessing student engagement in blended learning, where individual differences in learning experiences and perceptions are expected to produce considerable data variability. Despite its growing adoption in management and engineering research, EWM remains underutilised in blended learning engagement studies.

2.3.2 DEMATEL for Causal Analysis

DEMATEL is a widely used causal analysis technique that enables researchers to identify and map the cause-and-effect relationships among interdependent criteria within complex systems [21]. Unlike ranking-based MCDM methods, DEMATEL focuses on understanding the structural relationships between criteria, classifying them into cause groups, which exert influence on other criteria, and effect groups, which are primarily influenced by other criteria. In the context of blended learning research, DEMATEL has been applied to examine causal relationships among engagement-related criteria, revealing that instructional design, interaction quality, and technology support frequently emerge as influential cause factors that drive other engagement outcomes such as student participation and learning satisfaction [19]. By distinguishing between driving and outcome factors, DEMATEL enables educators and institutional policymakers to prioritise their interventions and allocate resources more strategically to the criteria that are most likely to produce systemic improvements in student engagement.

2.4 Integrated EWM-DEMATEL Approach

The integration of EWM and DEMATEL offers a more comprehensive and robust analytical framework for evaluating student engagement in blended learning than either method applied independently. While EWM provides an objective, data-driven basis for determining the relative importance of engagement criteria, DEMATEL reveals the causal structure and interdependencies among these criteria, enabling a simultaneous assessment of both criterion significance and system dynamics [11]. The combined approach is particularly well-suited to the study of student engagement in blended learning, where engagement criteria are known to be multidimensional, interrelated, and mutually reinforcing.

A review of existing MCDM-based studies on blended learning engagement reveals that no prior study [7, 8] has directly combined EWM with DEMATEL to evaluate student engagement criteria in a higher education context. Most existing integrated MCDM studies either combine Analytic Hierarchy Process (AHP) with Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) or apply DEMATEL independently without incorporating an objective weighting component. This represents a significant methodological gap, as the absence of objective criteria weighting limits the reliability of causal analyses and the validity of prioritisation findings. The present study addresses this gap by proposing and implementing an integrated EWM-DEMATEL framework that combines objective criteria weighting with causal relationship analysis, thereby providing a more complete and systematic evaluation of student engagement in blended learning. Although DEMATEL has been applied in blended learning research to examine causal relationships among criteria, its integration with objective, data-driven weighting methods such as EWM remains largely absent from the literature. This study addresses these gaps by proposing an integrated EWM-DEMATEL framework that combines objective criteria weighting with causal relationship analysis, offering a more systematic and rigorous approach to evaluating student engagement in blended learning environments.

3. Methodology

The section consists of the process of evaluating the criteria of student's engagement in blended learning using an integration of EWM and DEMATEL. Figure 1 illustrates the research framework adopted in this study. The process begins with the identification of engagement criteria from the existing literature, followed by data collection and screening to ensure that only qualified respondents are retained for analysis. The screened data are then simultaneously processed through two analytical methods, i.e., DEMATEL, which maps the causal relationships among the criteria, and EWM, which objectively determines the weight of each criterion based on data variability. The results from both methods are subsequently integrated using a geometric mean approach to derive combined weights, which are then used to produce the final ranking of the eight engagement criteria.

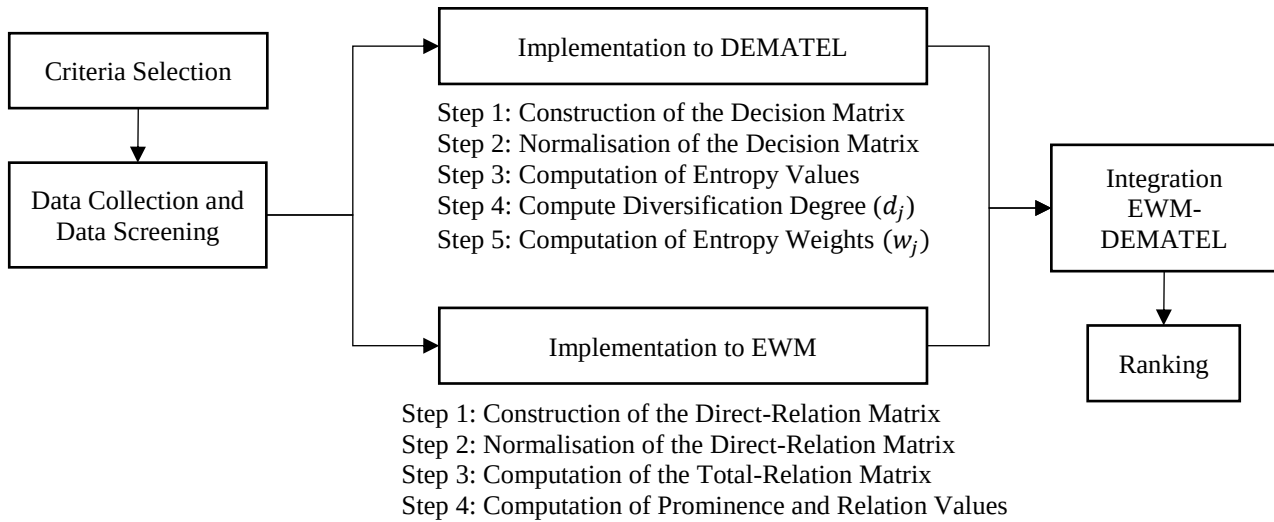


Figure 1. Research framework for evaluating students' engagement in blended learning using an integrated EWM-DEMATEL approach.

3.1 Identification of Engagement Criteria

Eight engagement criteria identified from the literature review (Section 2.2) were adopted in this study, namely Behavioral Engagement (C1), Cognitive Engagement (C2), Emotional Engagement (C3), Interaction Quality (C4), Instructional Design (C5), Technology Support (C6), Assessment and Feedback (C7), and Learning Satisfaction (C8).

3.2 Data Collection and Data Screening

A structured questionnaire was developed comprising five sections: Section A (declaration and informed consent), Section B (demographic and background information), Section C (24 engagement items rated on a five-point Likert scale from 1 = Strongly Disagree to 5 = Strongly Agree, serving as input for EWM), Section D (direct-relation assessment matrix for DEMATEL, rated from 0 = No Influence to 4 = Very High Influence), and Section E (closing acknowledgement). The survey was administered online via Google Forms to undergraduate students at UiTM, Negeri Sembilan Branch, Seremban Campus, with informed consent obtained from all respondents. Responses were then screened to retain only those who reported experience with more than three blended learning courses, ensuring the dataset reflected informed and relevant engagement experiences. A total of 99 undergraduate students participated in the survey. After screening, 58 responses met the criteria, yielding a response rate of 58.6% of respondents met the screening criteria and were selected for the subsequent EWM and DEMATEL analyses.

3.3 Application of the EWM

The EWM procedure adopted in this study follows the analytical framework outlined by Jiang et al. [11] and consists of five steps.

Step 1: Construction of the Decision Matrix

The first step in EWM is to construct the decision matrix $X = [x_{ij}]_{n \times m}$, where $n = 58$ denotes the number of respondents and $m = 8$ denotes the number of engagement criteria. Each element x_{ij} represents the average Likert-scale score assigned by respondent i to criterion j , calculated by averaging the three Likert-scale items measuring each criterion. For example, the score for Respondent 1 (R1) under Behavioral Engagement (C1), with three item scores of 5, 4, and 5, yields:

$$x_{11} = \frac{5 + 4 + 5}{3} = \frac{14}{3} = 4.67 \quad (1)$$

The same procedure was applied to all respondents and criteria. Table 2 presents the full decision matrix.

Table 2. Decision matrix of average Likert-scale scores for selected respondents across eight engagement criteria

Respondent	C1	C2	C3	C4	C5	C6	C7	C8
R1	4.67	4.33	4.00	4.00	4.00	4.00	4.00	4.00
R2	3.33	3.33	3.33	3.33	3.67	3.67	3.67	3.67
R3	3.33	4.00	3.67	3.00	3.00	4.00	3.00	4.67
R4	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
R5	4.33	4.67	4.33	4.33	4.67	4.00	3.67	4.67
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
R58	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00

Step 2: Normalisation of the Decision Matrix

The decision matrix was normalised to obtain the proportion of each criterion value using the following formula:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^n x_{ij}} \quad (2)$$

where p_{ij} represents the normalised value of criterion j for respondent i . For example, the normalised value for Respondent 1 (R1) under Behavioral Engagement (C1) is calculated by dividing R1's score (4.67) by the sum of all 58 respondents' scores under C1 (248.53):

$$p_{11} = \frac{4.67}{248.53} = 0.0188 \quad (3)$$

The same procedure was applied to all respondents and criteria, ensuring that each column sums to 1.0000. Table 3 presents the normalised matrix.

Table 3. Normalised decision matrix for the 58 respondents across eight engagement criteria

Respondent	C1	C2	C3	C4	C5	C6	C7	C8
R1	0.0188	0.0184	0.0177	0.0174	0.0171	0.0166	0.0173	0.0171
R2	0.0134	0.0142	0.0148	0.0145	0.0157	0.0152	0.0159	0.0156
R3	0.0134	0.0170	0.0163	0.0130	0.0128	0.0166	0.0130	0.0199
R4	0.0201	0.0213	0.0222	0.0217	0.0213	0.0208	0.0216	0.0213
R5	0.0175	0.0199	0.0192	0.0188	0.0199	0.0166	0.0159	0.0199
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
R58	0.0201	0.0128	0.0133	0.0174	0.0213	0.0166	0.0173	0.0171
Sum	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Step 3: Computation of Entropy Values

The entropy value (e_j) for each criterion was computed using the standard entropy formula:

$$e_j = -k \sum_{i=1}^n p_{ij} \ln(p_{ij}) \quad (4)$$

where $k = \frac{1}{\ln(n)} = \frac{1}{\ln(58)} = 0.2441$ is a constant that ensures $0 \leq e_j \leq 1$, and p_{ij} is the normalized value obtained previously. For example, the entropy value for C1 was computed by summing the product of each normalized value p_{i1} and its natural logarithm $\ln(p_{i1})$ across all selected respondents, then multiplying by $-k$:

$$e_1 = -0.2441 \times \sum_{i=1}^{58} p_{i1} \ln(p_{i1}) = -0.2441 \times (-4.0878) = 0.9975 \quad (5)$$

The same procedure was applied to all eight criteria, yielding the entropy values presented in Table 4.

Table 4. Entropy values for each engagement criterion

Criteria	$\sum_{i=1}^n p_{ij} \ln(p_{ij})$	$e_j = -0.2441 \sum_{i=1}^n p_{ij} \ln(p_{ij})$
Behavioral Engagement (C1)	-4.0878	0.9975
Cognitive Engagement (C2)	-4.0841	0.9966
Emotional Engagement (C3)	-4.0803	0.9957
Interaction Quality (C4)	-4.0788	0.9954
Instructional Design (C5)	-4.0873	0.9974
Technology Support (C6)	-4.0882	0.9976
Assessment and Feedback (C7)	-4.0859	0.9972
Learning Satisfaction (C8)	-4.0819	0.9960

Step 4: Compute Diversification Degree (d_j)

The diversification degree (d_j) measures the degree of variation for each criterion and is obtained by subtracting the entropy value from 1. A higher diversification degree indicates greater variability in respondent perceptions, implying that the criterion carries more discriminatory information and should be assigned a higher weight. The diversification degree was calculated as $d_j = 1 - e_j$. For example, the diversification degree for Behavioral Engagement (C1) is:

$$d_1 = 1 - 0.9975 = 0.0025 \quad (6)$$

The same procedure was applied to all eight criteria, as presented in Table 5.

Table 5. Diversification degree for each engagement criterion

Criteria	e_j	$d_j = 1 - e_j$
Behavioral Engagement (C1)	0.9975	0.0025
Cognitive Engagement (C2)	0.9966	0.0034
Emotional Engagement (C3)	0.9957	0.0043
Interaction Quality (C4)	0.9954	0.0046
Instructional Design (C5)	0.9974	0.0026
Technology Support (C6)	0.9976	0.0024
Assessment and Feedback (C7)	0.9972	0.0028
Learning Satisfaction (C8)	0.996	0.004
Total		0.0266

Step 5: Computation of Entropy Weights (w_j)

The entropy weight (w_j) for each criterion was calculated by dividing its diversification degree by the sum of all diversification degrees. This ensures that the weights are normalised and sum to 1, reflecting the relative objective importance of each criterion within the evaluation system. The entropy weight was computed as:

$$w_j = \frac{1 - e_j}{\sum_{j=1}^m (1 - e_j)} = \frac{d_j}{\sum_{j=1}^m d_j} \quad (7)$$

For example, the entropy weight for Behavioral Engagement (C1) is:

$$w_1 = \frac{0.0025}{0.0266} = 0.0949 \quad (8)$$

The same procedure was applied to all eight criteria, where the criterion with the highest entropy weight is considered the most important in the evaluation system. The final entropy weights and their corresponding rankings are presented in the next section.

3.4 Application of the DEMATEL Method

The DEMATEL method was applied to identify and map the causal relationships among the eight engagement criteria. This approach classifies criteria into cause-and-effect groups, enabling the identification of key driving factors within the blended learning engagement system. The DEMATEL procedure adopted in this study follows the framework outlined by Jiang et al. [11].

Step 1: Construction of the Direct-Relation Matrix

The direct-relation matrix $A = [a_{ij}]_{8 \times 8}$ was constructed based on responses from Section D of the questionnaire, where respondents rated the degree of direct influence between each pair of engagement criteria on a scale of 0 (No Influence) to 4 (Very High Influence). Each element a_{ij} represents the average score of all 58 respondents' ratings of the influence that criterion i exerts on criterion j . Diagonal elements were set to zero, indicating no self-influence. Table 6 presents the average direct-relation matrix.

Table 6. Direct-Relation Matrix $A = [a_{ij}]_{8 \times 8}$

	C1	C2	C3	C4	C5	C6	C7	C8
C1	0	3.1379	3.000	3.0862	2.9483	3.0345	3.1034	3.0862
C2	2.9828	0	3.0172	3	2.8966	2.8966	3.0345	3.069
C3	3.0862	2.9483	0	3.0345	2.9138	2.8966	2.9655	3.000
C4	3.1379	3.0517	3.000	0	2.931	2.9138	3.1724	3.0517
C5	3.2241	3.0517	3.069	3.069	0	2.9138	3.0345	3.1552
C6	3.2069	2.9828	3.1207	2.9655	3.0862	0	3	3.0345
C7	3.0862	3.0345	3.0345	2.9483	2.9655	2.931	0	3.1207
C8	3.1897	2.9655	3.1034	3.0862	3.069	2.9655	3.1034	0

Step 2: Normalisation of the Direct-Relation Matrix

The direct-relation matrix (A) was normalised by dividing each element by the maximum row sum. The maximum row sum was identified as 21.5172 (C5, Instructional Design). The normalisation formula is:

$$X = \frac{A}{\max_{1 \leq i \leq n} \sum_{j=1}^n a_{ij}} = \frac{A}{21.5172} \quad (9)$$

For example, the normalised value for the influence of C1 on C2 is calculated by dividing a_{12} (3.1379) by the maximum row sum (21.5172):

$$x_{12} = \frac{3.1379}{21.5172} = 0.1458 \quad (10)$$

The same procedure was applied to all elements in matrix A , producing the normalised direct-relation matrix (X) presented in Table 7.

Table 7. Normalised Direct-Relation Matrix X

	C1	C2	C3	C4	C5	C6	C7	C8
C1	0	0.1458	0.1394	0.1434	0.137	0.141	0.1442	0.1434
C2	0.1386	0	0.1402	0.1394	0.1346	0.1346	0.141	0.1426
C3	0.1434	0.137	0	0.141	0.1354	0.1346	0.1378	0.1394
C4	0.1458	0.1418	0.1394	0	0.1362	0.1354	0.1474	0.1418
C5	0.1498	0.1418	0.1426	0.1426	0	0.1354	0.141	0.1466
C6	0.149	0.1386	0.145	0.1378	0.1434	0	0.1394	0.141
C7	0.1434	0.141	0.141	0.137	0.1378	0.1362	0	0.145
C8	0.1482	0.1378	0.1442	0.1434	0.1426	0.1378	0.1442	0

Step 3: Computation of the Total-Relation Matrix

The total-relation matrix (T) was derived using the following formula, which captures both direct and indirect influences among all criteria:

$$T = X(I - X)^{-1} \quad (11)$$

where I denotes the identity matrix and X is the normalised direct-relation matrix obtained in Step 2. Each element of the total-relation matrix T is denoted as t_{ij} . For example, the total influence of C1 on C2 in the total-relation matrix is computed as $t_{12} = 9.5875$, which captures not only the direct effect of C1 on C2 ($x_{12} = 0.1458$) but also all indirect effects mediated through other criteria. The same matrix operation was applied to all elements simultaneously through the inverse matrix calculation, producing the total-relation matrix (T) presented in Table 8.

Table 8. Total-Relation Matrix (T)

	C1	C2	C3	C4	C5	C6	C7	C8
C1	9.7469	9.5875	9.6477	9.5923	9.4364	9.34	9.6808	9.7193
C2	9.6686	9.266	9.4528	9.395	9.2433	9.1459	9.4823	9.5218
C3	9.6523	9.3671	9.3102	9.3767	9.2247	9.1269	9.4601	9.4996
C4	9.8191	9.531	9.5939	9.4134	9.3831	9.2836	9.6293	9.6639
C5	9.9265	9.6322	9.6983	9.6396	9.3629	9.3822	9.7266	9.7703
C6	9.8778	9.583	9.6531	9.5892	9.4424	9.2175	9.6782	9.7186
C7	9.7627	9.4773	9.5417	9.4809	9.3321	9.2325	9.4472	9.6126
C8	9.9114	9.6156	9.6859	9.6267	9.4744	9.3709	9.7154	9.6287

Step 4: Computation of Prominence and Relation Values

For each criterion i , the row sum (D_i) and column sum (R_i) of the total-relation matrix T were computed as:

$$D_i = \sum_{j=1}^n t_{ij}, R_i = \sum_{j=1}^n t_{ji} \quad (12)$$

The prominence value ($D_i + R_i$) indicates the overall significance of criterion i within the system, while the relation value ($D_i - R_i$) determines its causal classification. Criteria with positive ($D_i - R_i$) values are classified as cause factors, indicating that they exert greater influence on other criteria, while those with negative values are classified as effect factors.

For example, the prominence and relation values for Instructional Design (C5) are computed as follows:

$$\begin{aligned} D_5 &= 9.9265 + 9.6322 + 9.6983 + 9.6396 + 9.3629 + 9.3822 + 9.7266 + 9.7703 = 77.1386 \\ R_5 &= 9.4364 + 9.2433 + 9.2247 + 9.3831 + 9.3629 + 9.4424 + 9.3321 + 9.4744 = 74.8993 \end{aligned}$$

$$D_5 + R_5 = 77.1386 + 74.8993 = 152.0379$$

$$D_5 - R_5 = 77.1386 - 74.8993 = +2.2393 \text{ (Cause factor)}$$

The complete prominence and relation values for all eight criteria are presented in the next section.

3.5 Integration of EWM and DEMATEL Results

To derive a comprehensive and robust evaluation of the engagement criteria, the weights obtained from EWM and the prominence values derived from DEMATEL were integrated using a multiplicative synthesis approach as proposed by Jiang et al. [11]. The DEMATEL prominence values were first normalised to obtain comparable weights. The prominence values ($D_i + R_i$) obtained from the DEMATEL analysis were first normalised to derive comparable DEMATEL weights ($W_{DEMATEL}$) for each criterion. The normalisation was performed by dividing each criterion's prominence value by the sum of all prominence values, as follows:

$$W_{DEMATEL_j} = \frac{(D_j + R_j)}{\sum_{j=1}^m (D_j + R_j)} \quad (13)$$

The sum of all prominence values is:

$$\begin{aligned} \sum (D_j + R_j) &= 155.1162 + 151.2354 + 151.6013 + 152.4312 + 152.0379 + 150.8592 + 152.7070 \\ &\quad + 154.1637 = 1219.9519 \end{aligned} \quad (14)$$

For example, the normalised DEMATEL weight for Behavioral Engagement (C1) is:

$$W_{DEMATEL_1} = \frac{155.1162}{1219.9519} = 0.1271 \quad (15)$$

The same procedure was applied to all eight criteria. Table 9 presents the normalised DEMATEL weights.

Table 9. Normalised DEMATEL weights

Criteria	D+R	$W_{DEMATEL_j}$
Behavioral Engagement (C1)	155.1162	0.1271
Cognitive Engagement (C2)	151.2354	0.1239
Emotional Engagement (C3)	151.6013	0.1242
Interaction Quality (C4)	152.4312	0.1249
Instructional Design (C5)	152.0379	0.1246
Technology Support (C6)	150.8592	0.1236
Assessment and Feedback (C7)	152.7070	0.1252
Learning Satisfaction (C8)	154.1637	0.1263
Total	1219.952	1.0000

The combined weight ($W_{combined}$) for each criterion was then computed as:

$$W_{combined} = \sqrt{W_{EWM} \times W_{DEMATEL}} \quad (16)$$

where W_{EWM} represents the objective weight from EWM and $W_{DEMATEL}$ represents the normalised prominence weight from DEMATEL. For example, the combined weight for C1 is:

$$W_{combined_1} = \sqrt{0.0949 \times 0.1271} = \sqrt{0.012062} = 0.1098 \quad (17)$$

The same procedure was applied to all eight criteria. Then, the value of $W_{combined}$ is normalized. The integration results are presented in results and discussion section.

3.6 Ranking of Engagement Criteria

The final ranking of the eight engagement criteria was determined based on their combined weights. Criteria were ranked in descending order, with higher combined weights indicating greater overall importance in influencing students' engagement in blended learning. This ranking provides a clear and evidence-based prioritisation of engagement factors, serving as a foundation for the interpretation and discussion of findings. Entire calculation process was computed using MS Excel on personal computer.

4. Result and Discussion

4.1 EWM Results

The application of the EWM yielded objective weights for each of the eight engagement criteria based on the degree of informational variability present in the respondent data of UiTM, Negeri Sembilan Branch, Seremban Campus. The resulting weights and rankings are presented in Table 10.

Table 10. EWM weights and rankings

Criteria	d_j	w_j	Rank
Behavioral Engagement (C1)	0.0025	0.0949	7
Cognitive Engagement (C2)	0.0034	0.1288	4
Emotional Engagement (C3)	0.0043	0.1606	2
Interaction Quality (C4)	0.0046	0.1716	1
Instructional Design (C5)	0.0026	0.0969	6
Technology Support (C6)	0.0024	0.0902	8
Assessment and Feedback (C7)	0.0028	0.1063	5
Learning Satisfaction (C8)	0.004	0.1506	3
Total	0.0266	1.0000	

The EWM results indicate that Interaction Quality (C4) obtained the highest entropy weight ($w = 0.1716$), followed by Emotional Engagement (C3) ($w = 0.1606$) and Learning Satisfaction (C8) ($w = 0.1506$). These three criteria exhibited the greatest degree of variability across undergraduate's students of UiTM, Negeri Sembilan Branch, Seremban Campus, suggesting that student perceptions of these factors differ most considerably within the blended learning context, and therefore carry the highest discriminatory power in the evaluation system. Conversely, Technology Support (C6) received the lowest EWM weight ($w = 0.0902$), followed by Behavioral Engagement (C1) ($w = 0.0949$) and Instructional Design (C5) ($w = 0.0969$), indicating comparatively lower variability in respondent perceptions of these criteria. As seen, Interaction Quality (C4) obtained the highest entropy weight ($w_j = 0.1716$, Rank 1), reflecting the greatest variability in student perceptions regarding the effectiveness of interactions between students, instructors, and learning systems in blended learning environments, suggesting that students' experiences of communication and collaboration with instructors and peers differ considerably across individuals. Technology Support (C6) obtained the lowest entropy weight ($w_j = 0.0902$, Rank 8), indicating that respondents showed relatively consistent perceptions regarding the availability, reliability, and usability of technological infrastructure. Consequently, this criterion contributed less discriminating information to the objective weighting process than the other criteria. One possible explanation is that the university provides campus-wide WiFi coverage and supports a bring-your-own-device policy, enabling relatively uniform access to digital learning platforms. As a result, students may have experienced similar levels of Technology Support, leading to less variation in their responses.

4.2 DEMATEL Results

The DEMATEL analysis produced weights derived from the prominence values ($D_i + R_i$) of each criterion, reflecting its overall significance and influence within the causal structure of the blended learning engagement system. The normalised DEMATEL weights and rankings are presented in Table 11.

Table 11. DEMATEL Weights and Rankings of Engagement Criteria

Criteria	D	R	D+R	Rank	D-R	Group
Behavioral Engagement (C1)	76.7509	78.3653	155.1162	1	-1.6144	Effect
Cognitive Engagement (C2)	75.1758	76.0596	151.2354	7	-0.8838	Effect
Emotional Engagement (C3)	75.0176	76.5837	151.6013	6	-1.5661	Effect
Interaction Quality (C4)	76.3174	76.1138	152.4312	4	0.2036	Cause
Instructional Design (C5)	77.1386	74.8993	152.0379	5	2.2393	Cause
Technology Support (C6)	76.7597	74.0995	150.8592	8	2.6602	Cause
Assessment and Feedback (C7)	75.887	76.82	152.707	3	-0.9331	Effect
Learning Satisfaction (C8)	77.029	77.1348	154.1637	2	-0.1058	Effect

The DEMATEL analysis classified the eight engagement criteria into cause-and-effect groups based on their D-R values, as presented in Table 11. Technology Support (C6) emerged as the strongest cause factor ($D-R = +2.6602$), indicating that the availability, reliability, and usability of technological infrastructure exert the greatest net influence on other engagement criteria within the blended learning system for students of UiTM, Negeri Sembilan Branch, Seremban Campus. This finding suggests that although technology was perceived as relatively uniform in the EWM analysis, it nonetheless serves as a foundational structural driver that shapes other engagement dimensions — when technological infrastructure functions consistently and reliably, it enables students to focus on learning interactions, instructional activities, and emotional investment, thereby facilitating engagement across other criteria. Instructional Design (C5, $D-R = +2.2393$) and Interaction Quality (C4, $D-R = +0.2036$) were similarly identified as cause factors, reinforcing the view that the organisation of learning activities and the quality of student-instructor interaction serve as structural enablers that drive the broader engagement system.

In terms of prominence ($D+R$), Behavioral Engagement (C1) recorded the highest value ($D+R = 155.1162$, Rank 1), indicating that it is the most systemically involved criterion while being both highly influential and highly influenced by other criteria within the blended learning engagement system. However, its negative D-R value (-1.6144) classifies it as the most strongly influenced effect factor, suggesting that students' observable participation in blended learning activities, including attendance, task completion, and active involvement, is largely a downstream outcome shaped by the structural

cause factors rather than an independent driver of engagement. Conversely, Technology Support (C6) recorded the lowest prominence value ($D+R = 150.8592$, Rank 8) despite being the strongest cause factor, suggesting that while it exerts considerable one-way influence on other criteria, it is itself less influenced by other engagement dimensions within the system. This distinction between prominence and causal direction highlights the complementary nature of the EWM and DEMATEL analyses and reinforces the importance of integrating both methods to obtain a more complete understanding of the engagement system.

4.3 Integrated EWM-DEMATEL Results and Ranking

The combined weights derived from the integration of EWM and DEMATEL provide a comprehensive measure of each criterion's overall importance, incorporating both objective data variability and structural causal significance for evaluating blended learning engagement drivers among undergraduate's students of UiTM Negeri Sembilan, Seremban Campus. The integration results as presented in Table 12. Interaction Quality (C4) ranked first with the highest normalised combined weight (0.1475). Previous blended learning studies by [22], and [23] shows that the interaction is an essential determinant of student engagement and learning effectiveness. Consistent with these findings, respondents from UiTM Negeri Sembilan, Seremban Campus perceived interactions among students, instructors, and learning platforms as a key dimension contributing to positive blended learning experiences. Emotional Engagement (C3) ranked second (0.1423) and Learning Satisfaction (C8) ranked third (0.1390) by students of UiTM Negeri Sembilan, Seremban Campus, with both classified as effect factors in the DEMATEL analysis. The prominence of Emotional Engagement is supported by previous research [24] which identified a positive relationship between emotional engagement, psychological capital, and academic performance in a blended learning context. Similarly, Cheng et al. [25] highlighted that learning attitudes, curriculum design, and teaching methods significantly influence students' satisfaction with blended learning in higher education. These findings suggest that students' affective experiences and overall evaluations of blended learning are important dimensions shaped by the underlying causal factors within the engagement system. Furthermore, their relatively high EWM weights indicate greater variability in students' perceptions of these dimensions, suggesting that they provide substantial discriminatory information in the evaluation process and should be considered in engagement monitoring and improvement initiatives.

Table 12. Integrated EWM-DEMATEL Combined Weights and Final Rankings

Criteria	EWM Weight	DEMATEL Weight	Cause-Effect	Combined Weight	Normalised Weight	Final Rank
Behavioral Engagement (C1)	0.0949	0.1271	Effect	0.1098	0.1106	7
Cognitive Engagement (C2)	0.1288	0.1239	Effect	0.1264	0.1273	4
Emotional Engagement (C3)	0.1606	0.1242	Effect	0.1413	0.1423	2
Interaction Quality (C4)	0.1716	0.1249	Cause	0.1465	0.1475	1
Instructional Design (C5)	0.0969	0.1246	Cause	0.1099	0.1107	6
Technology Support (C6)	0.0902	0.1236	Cause	0.1056	0.1064	8
Assessment and Feedback (C7)	0.1063	0.1252	Effect	0.1154	0.1162	5
Learning Satisfaction (C8)	0.1506	0.1263	Effect	0.1380	0.1390	3

Notably, Technology Support (C6) ranked last (0.1064) in the final combined ranking despite being the strongest cause factor in the DEMATEL analysis. In this study, Technology Support refers to the availability, reliability, and usability of digital platforms, which represents an essential foundation for effective blended learning implementation. However, the relatively low EWM weight does not indicate that Technology Support is insignificant; rather, it suggests that respondents from UiTM Negeri Sembilan, Seremban Campus demonstrated relatively consistent perceptions regarding digital platform availability, reliability, and usability, resulting in lower discriminatory power among the criteria. This finding may be attributed to the increasing availability and normalisation of digital learning platforms in higher education, particularly following the rapid digital transformation during the COVID-19 pandemic. Furthermore, Cheng et al. [25] highlighted that students' satisfaction with blended learning is influenced by learning attitudes, curriculum design, and teaching methods, indicating that students' blended learning experiences are shaped by multiple dimensions beyond technological access alone. Therefore, Technology Support may function as a fundamental enabling condition for blended learning, while variations in student engagement are more strongly reflected through interactional and affective dimensions.

5. Conclusions

This study applied an integrated EWM and DEMATEL framework to evaluate eight key factors influencing students' engagement in blended learning at UiTM, Negeri Sembilan Branch, Seremban Campus. The eight criteria examined were Behavioral Engagement, Cognitive Engagement, Emotional Engagement, Interaction Quality, Instructional Design, Technology Support, Assessment and Feedback, and Learning Satisfaction. By combining objective criteria weighing

through EWM with causal relationship analysis through DEMATEL, this study provided a systematic and comprehensive evaluation of student engagement that addresses the methodological limitations of existing single method approaches in blended learning research. The EWM analysis identified Interaction Quality, Emotional Engagement, and Learning Satisfaction as the highest-weighted criteria, reflecting the greatest variability in student perceptions across these dimensions. The DEMATEL analysis classified Technology Support and Instructional Design as the primary cause factors driving the engagement system, while Behavioral Engagement, Emotional Engagement, Assessment and Feedback, Cognitive Engagement, and Learning Satisfaction were identified as effect factors that respond to improvements in the structural drivers. The integrated EWM-DEMATEL ranking further placed Interaction Quality as the most critical engagement criterion overall, followed by Emotional Engagement and Learning Satisfaction, providing an evidence-based prioritisation of engagement factors that simultaneously accounts for both objective data variability and causal structural significance.

Despite its contributions, this study has several limitations that should be acknowledged. The sample was limited to undergraduate students at a single campus, which may restrict the generalisability of the findings to other institutions or academic disciplines. Additionally, the reliance on self-reported questionnaire data introduces the possibility of response bias. Future research should consider extending this framework to broader institutional contexts and diverse academic disciplines to enhance the generalisability of findings. The incorporation of qualitative methods alongside the quantitative EWM-DEMATEL approach may also provide deeper insights into the contextual factors shaping the causal relationships identified in this study. Furthermore, the application of fuzzy set theory to account for uncertainty in respondent judgements represents a promising avenue for further methodological development.

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Declaration of Competing Interest

The authors declare no conflict of interest.

CRedit Authorship Contribution Statement

Daniel Jazreezal Razali (Methodology; Writing – original draft)

Zati Aqmar Zaharudin (Supervision; Validation; Writing – review & editing)

Muhammad Nur Zakuwan Mohamad Asri (Writing – review & editing)

Availability of the Data and Materials

The data used to support the findings of this study are included within the article.

Ethical Declarations

This study has received ethical approval from the Ethics Committee of Universiti Teknologi MARA Cawangan Negeri Sembilan (REC/1902/2026).

Generative Artificial Intelligence Declarations

The authors claim that artificially intelligent-assisted technologies, such as generative AI, were not used to generate content, ideas, or theories. We have just utilised AI to enhance readability and refine the language. This was used with extreme human control and oversight. The authors take full responsibility for reviewing and approving the content.

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Critical issues for the authors

- Author format: the APA-style commas and ampersands in [2], [3], [4], [5], [7], [8], [16], [18], [19] and stray commas in [21], [23], [25] were removed; Vancouver uses "Surname Initials" separated by commas with no "&".
- [10] and [20] have seven authors; Vancouver lists the first six followed by "et al."

- [3], [11], [14] Conference papers require the Vancouver conference structure: In: editors. Conference title; date; place. Publisher; year. p. pages.
- [7] Thesis restructured to Vancouver form: Author. Title [dissertation]. Place: University; Year.
- [12], [13], [18] Neutrosophic Sets and Systems assigns page ranges within each volume; the numbers 13, 30 and 35 look like article positions, not pages. Replace them with the actual page ranges.
- [14] and [19] have near-identical titles ("Blended learning quality measurement system using ..."), differing only in the method. Check [19] carefully for originality and journal standing before citing both.
- [18] The title appears to be missing a word ("approach [for] college English"); verify against the article.
- [20] (heat pump water heater) and [21] (performance indicators) fall outside the education domain; confirm they are cited for the entropy weight and DEMATEL methods only.
- [1] Vancouver requires the date of citation for web sources; it was missing.

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