Strategic Leverage Points in Blended Learning: A Systems Science Approach Using Grey-DEMATEL-ISM-MICMAC Framework in Higher Education

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Abstract: E-learning has emerged as a cornerstone of contemporary higher education, offering flexible and technology-mediated environments that accommodate modern learning needs. Among its various modalities, blended learning (BL), which strategically integrates face-to-face and online instruction, has become a pivotal approach in higher education for enhancing learning outcomes and fostering talent cultivation. However, its successful implementation depends on the coordinated interaction of individual, technological, environmental, and course dimensions, constituting a complex network of interdependent factors that often remain fragmented in practice. Existing studies typically examine these factors in isolation and commonly rely on linear analytical approaches, providing limited insights into the systematic, comprehensive, and hierarchical understanding of the interrelationships among them. Understanding these structural interrelationships is therefore essential for identifying strategic leverage points that can optimise system performance and ensure the sustainable success of BL initiatives. To address this gap, this study proposes a systems science-based analytical framework that integrates the Grey Decision-Making Trial and Evaluation Laboratory (Grey-DEMATEL), Interpretive Structural Modelling (ISM), and Matrix Impact Cross Multiplication Applied to Classification (MICMAC). This integrated approach enables comprehensive and data-driven modelling of the causal parameters, hierarchical structure, and driving-dependence relationships among critical success factors of BL. First, ten critical success factors were identified through a systematic literature review and were then pairwise evaluated by twelve experts from a higher education institution in Thailand. Grey-DEMATEL was subsequently employed to quantify the causal properties and relative significance of these factors, while ISM was applied to construct a multi-layer hierarchical structure. MICMAC analysis further categorised the factors according to their driving and dependence powers. The results reveal a three-layer hierarchical structure of BL critical success factors, where policy support ($R - C$ = 2.78), system quality ($R - C$ = 1.73), and technical support (R – C = 1.62) serve as key causal drivers, forming the institutional and technological foundation of the BL system. Course design and technology experience act as mediating linkages connecting institutional mechanisms with learning outcomes, while attitude, perceived usefulness, and interaction represent outcome-level indicators of system performance. Among these factors, course design exhibits the highest level of centrality value ($R + C$ = 18.6) with the causal structure. The findings extend the understanding of the causal hierarchy and strategic leverage points for achieving BL success, illustrate how institutional and technological investment are realised through course design to improve individual experience. The study offers actionable insights for policymakers and instructional designers to inform data-driven decision-making and strategic planning in higher education, as well as how this is implemented at the level of the individual academic.

Keywords: Blended learning, Higher education, Multi-criteria decision analysis, Critical success factors, Systems science, Grey-DEMATEL-ISM-MICMAC

1. Introduction

The pervasive integration of digital technologies into daily life has not only profoundly reshaped how individuals live and interact but also transformed the creation and dissemination of knowledge (Liu, 2025). These ongoing transformations place increasing demands on higher education institutions (HEIs) to adapt proactively, not only in terms of delivery models, but also with respect to pedagogical approaches, instructional strategies, and teaching methodologies (Samala, Papadakis and Rawas, 2025). Within this context, blended learning has gained growing recognition for its potential to address diverse learning needs and enhance educational effectiveness (Mizza, Reese and Malouche, 2025), positioning it as a pivotal approach in shaping the educational frontier (Samala, Papadakis and Rawas, 2025; Verma et al., 2025). Blended learning (BL) is a pedagogical approach that integrates face-to-face instruction with online digital learning through appropriate alignment and balance (Castro, 2019). Stemming from the convergence of technological advancements and pedagogical theories, BL offers a flexible instructional paradigm that adapts to changing educational environments and accommodates diverse learning preferences. In recent years, a growing number of HEIs have embraced and implemented BL as

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a key instructional strategy (Chen, 2022), recognising its capacity to foster lifelong learning and adaptability in an increasingly digitalised society (Dziuban et al., 2011).

As BL implementation matures, scholarly attention has shifted from adoption drivers to post-adoption effectiveness, particularly in identifying the factors that critically determine successful outcomes. Previous studies have explored various critical success factors, including course design quality (Huang, Kuang and Ling, 2022), classroom interaction (Majeed and Rehan Dar, 2022), the stability and information quality of learning management systems (Prifti, 2022), appropriate technological support (Su et al., 2023), and strong managerial support (Al-Mekhlafi et al., 2025; Zhao and Song, 2021). Empirical evidence suggests that the success of BL emerges from the interactions of multiple dimensions rather than from any single factor (Mielikäinen, 2022; Min and Yu, 2023). Nevertheless, most existing empirical studies rely primarily on linear analytical approaches such as structural equation modelling (SEM) and regression analysis (McCarthy and Palmer, 2023). While these methods are helpful for estimating associations among variables and revealing the significance of path effects, they are limited by linear assumptions and thus fail to capture potential nonlinear dynamics and feedback mechanisms among factors (Feng et al., 2024). Moreover, they typically examine single-layer relationships between independent and dependent variables (Hair et al., 2021), lacking the capacity to represent hierarchical structures or causal feedback loops. This methodological limitation prevents a thorough assessment of the status and structural interrelations of the factors within the system. In other words, the current research has yet to provide a systematic, comprehensive, and hierarchical understanding of the BL critical success factors in higher education. As technology-enhanced education continues to evolve, ongoing research remains necessary to deepen the understanding of effective teaching and learning practices and to support continuous refinement of BL initiatives (Samala, Papadakis and Rawas, 2025).

To address this gap, this study integrates Grey System theory with three complementary analytical methods, including Decision-Making Trial and Evaluation Laboratory (DEMATEL), Interpretive Structural Modelling (ISM), and Matrix-Based Cross-Impact Multiplication Applied to Classification (MICMAC), to construct a three-stage systemic framework that enables a comprehensive, hierarchical, and data-driven analysis of critical success factors in BL systems. By integrating these methods, the proposed framework provides a systematic approach to reveal the causal relationships, hierarchical structure, and driving-dependence mechanisms among critical success factors in BL systems. This integrated approach has been widely applied in complex system studies across various fields, including construction engineering (Zhang et al., 2024), supply chain management (Primadasa et al., 2025), and sustainable development (Bagherian et al., 2024), demonstrating its capacity to analyse systems characterised by numerous interacting factors, complex organisational interdependencies, and nonlinear causal feedback (Liu, Hu and Huang, 2024). In recent years, educational researchers have also increasingly employed such Multi-Criteria Decision Analysis (MCDA) techniques to explore interrelated factors in digital learning contexts, including virtual learning (Chuaphun and Samanchuen, 2024), simulation-based learning adoption (Asadi et al., 2024), and online learning quality (Zhou, Tang and Liu, 2025). However, prior studies have typically focused on simple causal analyses rather than a holistic exploration of system dynamics, and few studies have integrated Grey-DEMATEL, ISM, and MICMAC within a unified analytical framework to examine complex educational systems.

BL systems, by contrast, are inherently complex, multidimensional, and interdependent, requiring a systematic and comprehensive analytical approach to identify the cause-and-effect parameters and structural hierarchy relationships, and reveal the strategic leverage points necessary for effective improvement. To address this issue, the present study integrates three analytical methods into a unified framework that captures causal influence, hierarchical structure, and driving-dependence patterns. Accordingly, the following research questions are formulated:

RQ1: What causal relationships exist among the critical success factors of BL in higher education?

RQ2: What hierarchical structure characterises the relationships among these critical success factors?

RQ3: How can these critical success factors be categorised according to their driving-dependence powers, and which factors can be identified as strategic leverage points for improving BL effectiveness in higher education?

Specifically, Grey-DEMATEL enables the identification and evaluation of causal relationships and the strength of influence among factors, while accounting for uncertainty in expert judgments and providing a detailed visualisation of interdependencies (Bai and Sarkis, 2013). ISM utilises graph theory to partition complex systems into distinct elements (Feng et al., 2024) and constructs a multi-tiered structural model to enhance comprehension and analysis (Asadi et al., 2024). MICMAC analysis evaluates the driving and dependence powers of each factor and classifies them into four categories (Zhang et al., 2024), thereby identifying the most strategically valuable leverage points within the system (Almerino et al., 2024). This integrated approach enhances the analytical depth and interpretability of the results, providing a systemic and transparent understanding of the interconnections between critical success factors in BL environments.

This study extends existing research by employing Grey-DEMATEL, ISM, and MICMAC in an integrated manner within the educational context. The novelty of this work lies in its structured systems-modelling approach, which transcends linear analytical boundaries and reveals the complex causal chains and hierarchical structures underlying BL practices in HEIs. The results aim to provide a decision-support framework that is both systematic and actionable, enabling educational administrators and instructors to identify and prioritise strategic leverage points for improvement, thereby enhancing the overall effectiveness of BL initiatives.

2. Critical Success Factors of Blended Learning in Higher Education

The concept of critical success factors refers to the essential conditions or variables that determine the success of an organisation or system (Pollard and Cater-Steel, 2009). By taking critical success factors into account, organisations can identify the primary obstacles and prevent potential failures (Alkarney and Albraithen, 2018), and stakeholders can achieve better outcomes (Alqahtani and Rajkhan, 2020; Min and Yu, 2023). In essence, critical success factors are the elements that must be achieved for an organisation to be successful in attaining its desired goals (Selim, 2007). The critical success factors of BL are considered key influencing factors that significantly impact the effectiveness and outcomes of BL initiatives, which are reflected in the students' learning experience, performance, and satisfaction (Ghazal, Al-Samarraie and Aldowah, 2018; Min and Yu, 2023).

In order to determine the critical success factors of BL in HEIs, this study draws on the results of a systematic literature review (SLR) conducted by Liu and Yodmongkol (2023), following the approach outlined by Pattanasak et al. (2022). The relevant studies were retrieved from the Scopus database using the search string "blended-learning AND higher-education AND factor". The search was limited to conference proceedings and international journal publications between 2013 and 2023 to ensure research quality and relevance. Through the screening and refinement process, the initial set of 364 studies was narrowed down to 63 studies for in-depth analysis (Liu and Yodmongkol, 2023). The analysis focused on four dimensions based on the Complex Adaptive Blended Learning System (CABLS) framework (Wang, Han and Yang, 2015), including individual, technological, environmental, and course aspects. In addition to the SLR findings, recent international studies offer further context for understanding the critical success factors of BL. The evidence from higher education administrators and teachers across multiple European countries indicates that technological infrastructure, digital quality, and the availability of technical support and training are critical in enhancing BL effectiveness and student learning outcomes (Mohammadi, Paasivara and Kasurinen, 2025). At a broader level, bibliometric evidence from global higher education technology research suggests that technological and system quality, content quality, individual digital competence, and organizational-level technical support consistently underpin the successful implementation of technology-enhanced learning across diverse educational contexts (Samala, Papadakis and Rawas, 2025).

By synthesising the SLR findings with insights from recent international research, ten critical success factors with the highest frequency of occurrence within each dimension were identified, as presented in Table 1. Specifically, the individual dimension includes the competencies, perceptions, and attitudes of users involved in BL courses; the technological dimension encompasses the quality of digital systems and learning information; the environmental dimension reflects the institutional context, including policies and support mechanisms that facilitate BL implementation; and the course dimension represents the instructional design and interaction within BL courses. The selection of ten factors also aligns with the previous MCDA-based studies in educational contexts, which commonly analyse between 10 and 15 factors (Asadi et al., 2024; Chuaphun and Samanchuen, 2024) to maintain the analytical feasibility and interpretability of pairwise influence matrices.

Table 1: Critical success factors of blended learning in higher education

Factors	Code	Description	Reference
Computer self-efficacy	CSE	An individual's confidence in their capability to successfully utilize computers for educational tasks (Prifti, 2022).	(Katsarou, 2021; Prifti, 2022)
Technology experience	TE	The interaction and engagement individuals have with technology, involving the user's exposure to the system's functionality and the knowledge and skills the user gains from those interactions (Thompson, Compeau and Higgins, 2008).	(Al-Samarraie and Saeed, 2018; Alomari et al., 2020)

Factors	Code	Description	Reference
Perceived usefulness	PU	The degree to which the person perceives that blended learning, or its technology is a valuable and advantageous (Dakduk, Santalla-Banderali and Van Der Woude, 2018).	(Vo, Zhu and Diep, 2020; Wu and Liu, 2013)
Attitude	ATT	An individual's assessment of a specific behaviour, characterized by either favorable or unfavorable judgments (Wu et al., 2022).	(Acosta-Gonzaga and Ramirez-Arellano, 2021)
Interaction	INT	Timely and supportive communication that occurs during the learning process between teachers and students, and collaborative communication and activities that occur between peers in blended learning environment.	(Nortvig, Petersen and Balle, 2018; Taghizadeh and Hajhosseini, 2021)
System quality	SQ	Reliability, flexibility, integration, accessibility, timeliness, and integrity, which collectively ensure the system's effectiveness in meeting user needs and supporting their tasks (Li and Zhu, 2022).	(Majeed and Rehan Dar, 2022)
Information quality	INQ	The relevance, timeliness, accuracy, completeness, accessibility, adequacy, clarity, consistency, and format of content provided by an information system to its users (Ghazal, Al-Samarraie and Aldowah, 2018; Roca, Chiu and Martínez, 2006).	(Nikou and Maslov, 2023)
Policy support	PS	The establishment of guidelines, frameworks, and regulations that govern the implementation and operation of blended learning programs.	(Anthony et al., 2019; Galvis, 2018; Zhou, Smith and Al-Samarraie, 2023)
Technical support	TS	Support services for educators and learners in blended learning, encompassing training, guidance, and troubleshooting in technology use.	(Anthony et al., 2022; Bokolo Jr et al., 2020)
Course design	CD	The strategic creation and organization of learning content, technology, and activity to create quality learning environments and experiences for students.	(Huang, Kuang and Ling, 2022; Su et al., 2023)

3. Methodology

This study employed a structured system modelling approach that integrates Grey-DEMATEL, ISM, and MICMAC within the framework of systems science to analyse the BL critical success factors. This hybrid methodology enables a systematic examination of causal relationships and hierarchical structures among variables, thereby assisting decision-makers in identifying strategic leverage points for effective improvement. The methodological workflow is depicted in Figure 1.

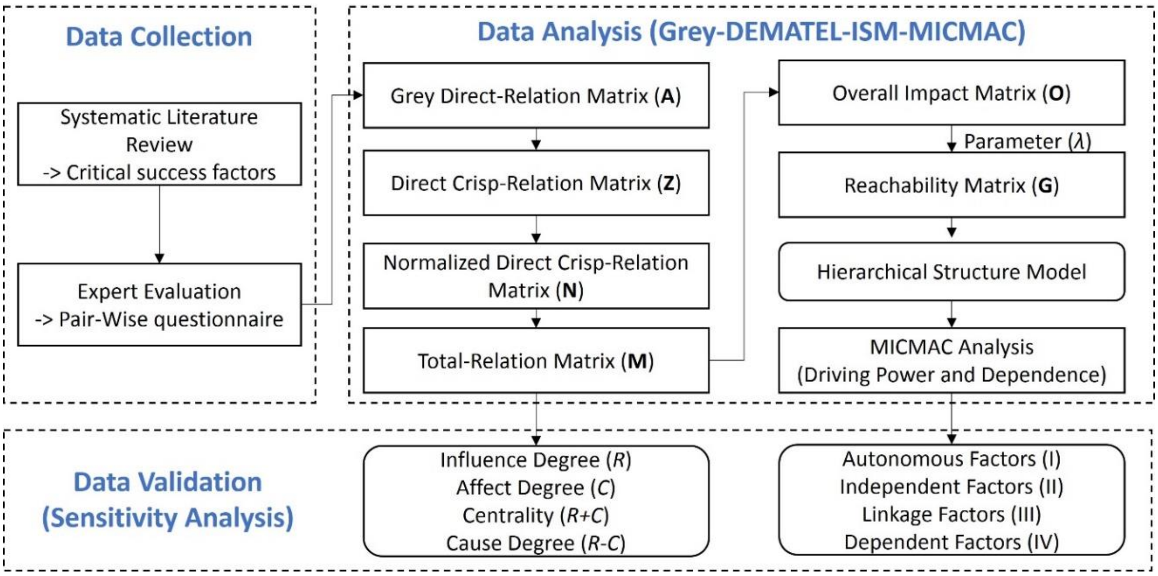

Figure 1: Workflow of Grey-DEMATEL-ISM-MICMAC methodology

The DEMATEL is a causal analysis technique based on expert judgment that identifies and visualises interrelationships among system variables (Aria, Jafari and Behifar, 2024). It quantifies the degree to which factors influence or are influenced by other factors through matrix computation and graphical representations (Dalvi-Esfahani et al., 2019), thereby capturing the causal relationships among system components (Aria, Jafari and Behifar, 2024) and the relatively significant levels of these relationships (Thakkar, 2021). It is considered a holistic and comprehensive method for analysing causal structures among factors (Lu, Huang and Wang, 2024). However, expert judgments are inevitably influenced by fuzziness and uncertainty in real-life situations (Liu et al., 2021), as well as by human bias, incomplete information, and inherent uncertainties (Pinili et al., 2024). To address these limitations, Grey system theory is incorporated into DEMATEL, which enhances the reliability, accuracy, and robustness of causal inference in uncertain environments (Deepu and Ravi, 2021). Despite its strength in revealing causal linkages, DEMATEL alone cannot intuitively depict the hierarchical structure of relationships within a system.

The ISM effectively complements this limitation by applying graph theory to decompose complex systems into structured, multi-level models (Feng et al., 2024). Through algebraic operations, ISM analyses the direct binary relationships among variables and applies Boolean logic to construct recursive and directed topologies (Lan et al., 2022). This process reveals the logical pathways linking foundational causal factors to higher-order outcome factors (Liu, Hu and Huang, 2024), thereby clarifying the hierarchical organisation and interdependence within the system. Nevertheless, the ISM is primarily oriented toward structural and macro-level exploration, and it does not quantify the relative contribution of each element to the system.

The MICMAC analysis further refines the ISM-derived structure by classifying factors according to their driving and dependence power (Du and He, 2025). Based on the principle of matrix multiplication, MICMAC categorises variables into four categories: autonomous, independent, linkage, and dependent, each exerting distinct effects on system dynamics, stability, and feedback (Bashir and Ojiako, 2020).

Taken together, the Grey-DEMATEL-ISM-MICMAC framework integrates the strengths of causal analysis, hierarchical modelling, and driving-dependence classification. This three-stage hybrid approach enables a systematic and holistic examination of the driving forces and interaction mechanisms within complex systems, thereby offering robust support for strategic decision-making.

3.1 Data Collection with Expert Evaluation

The first step involved identifying the factors or variables within the system as determined through the SLR and summarised in Table 1. An expert panel then conducted pairwise comparisons to assess the causal relationships among the ten critical success factors. In accordance with the data requirements of the DEMATEL method, an evaluation scale ranging from 0 to 4 was used to quantify causal influence (Pinili et al., 2024), and the corresponding grey values are presented in Table 2.

Table 2: Linguistic scale and corresponding grey values

Linguistic term	Influence score	Grey values
No influence	0	[0,0]
Very low influence	1	[0,0.25]
Low influence	2	[0.25,0.5]
High influence	3	[0.5,0.75]
Very high influence	4	[0.75,1]

The expert sampling technique was employed to select participants, ensuring that the data originated from individuals with specialised knowledge and relevant experience (Tuapawa, 2017). The specific criteria were established as follows: 1) individuals who hold a doctoral degree with more than five years of teaching experience in HEIs; 2) individuals who have conducted more than ten BL courses; and 3) individuals who have received teaching awards, honours, or other formal recognition for excellence in BL or e-learning. The invitation was issued to qualified experts via institutional email, accompanied by an official letter from the host organisation outlining the research objectives, procedures, and anticipated contributions. An information sheet and informed consent form were also provided, clearly stating the voluntary nature of participation, measures for confidentiality and data privacy, and the use of anonymised judgments for quantitative analysis and academic publication. Of the invited experts, twelve consented to participate, as detailed in Table 3. This sample size aligns with established methodological precedents in related studies, which have typically engaged between five and fifteen domain experts (Asadi et al., 2024; Khan et al., 2024).

Although all participating experts were affiliated with a single HEI in Thailand, prior MCDM studies indicate that the validity of expert judgments depends primarily on the diversity of experts' backgrounds, functional roles, experience, knowledge, and areas of specialisation (Du and Shen, 2024). This approach is consistent with Li and Xiao (2024) and Quiñones et al. (2020), who emphasise that multi-functional expert panels are more effective for identifying causal relationships in complex systems that help reduce bias and enhance the robustness of analytical results. As shown in Table 3, the expert panel in this study comprised members from different faculties and disciplinary backgrounds who occupied distinct functional roles, including instructional, management, and technical support roles. Several experts concurrently held multiple functional responsibilities, enabling cross-functional evaluation of causal relationships among critical success factors. In addition, this study incorporated grey theory and sensitivity analysis to further mitigate the uncertainty and subjectivity of expert judgments. As noted by Si et al. (2018), the integration of grey theory is particularly appropriate for systems that exhibit random uncertainty. Sensitivity analysis was subsequently conducted to assess the stability of the identified structure, thereby enhancing the robustness of the analytical results.

Table 3: Expert demographic information

Category	Sub-Category	Percentage
Position/ Role	Lecturer	8.33%
	Assistant Professor	50.00%
	Associate Professor	41.67%
Teaching Experience	5-15 years	33.33%
	16-25 years	16.67%
	More than 25 years	50.00%
Area of Expertise	E-learning/ Blended Learning	50.00%
	Educational Technology	25.00%
	Pedagogical Innovation	25.00%
Function Roles	Instructional	100.00%
	Management	50.00%
	Technical Support	25.00%

3.2 Data Analysis with Grey-DEMATEL-ISM-MICMAC Approach

The Grey-DEMATEL method was implemented in accordance with the methodology outlined by Raj and Sah (2019). The DEMATEL method analyses complex systems by identifying and evaluating pairwise relationships among a set of factors $x = \{x_i | i = 1,2, \dots ,10\}$. Grey systems are characterised by the use of grey numbers, grey equations, and grey matrices (Deepu and Ravi, 2021). In Grey system theory, $\otimes x$ represents a grey number, which is an interval defined by known lower upper $\overline{\otimes} x$ and lower $\underline{\otimes} x$ bound, while the distribution information of $\otimes x$ remains unknown. Specifically, $\otimes x$ is constrained within the range $[\underline{\otimes} x, \overline{\otimes} x]$, where $\underline{\otimes} x$ and $\overline{\otimes} x$ represent the lower and the upper limits, respectively. The influence scores of factors i on factors j $(\forall i, j)$ were obtained from the experts and then converted into corresponding grey values.

Step 1: the Grey direct-relation matrix (*A*) is calculated using equation (1), assigning equal weight to all twelve experts to ensure that each expert's judgment contributed equally to the aggregated evaluation.

$$\otimes x_{ij}^{12} = \left(\frac{\sum_{12} \underline{\otimes} x_{ij}^{12}}{12}, \frac{\sum_{12} \overline{\otimes} x_{ij}^{12}}{12} \right) \quad (1)$$

Step 2: the direct crisp-relation matrix (*Z*) is constructed using the Converting Fuzzy Data into Crisp Scores (CFCS) method (Opricovic and Tzeng, 2003), which transforms grey numbers into crisp values through a three-step procedure, as outlined below.

- Normalization

$$\Delta_{min}^{max} = \max_j \overline{\otimes} x_{ij} - \min_j \underline{\otimes} x_{ij} \quad (2)$$

$$\underline{\otimes}\bar{x}_{ij} = (\underline{\otimes}x_{ij} - \min_{j}\underline{\otimes}x_{ij})/\Delta_{min}^{max} \tag{3}$$

$$\overline{\otimes}\bar{x}_{ij} = (\overline{\otimes}x_{ij} - \min_{j}\underline{\otimes}x_{ij})/\Delta_{min}^{max} \tag{4}$$

- Calculating the normalized crisp value

$$y_{ij} = \frac{\underline{\otimes}\bar{x}_{ij}(1 - \underline{\otimes}\bar{x}_{ij}) + \overline{\otimes}\bar{x}_{ij} \cdot \overline{\otimes}\bar{x}_{ij}}{1 - \underline{\otimes}\bar{x}_{ij} + \overline{\otimes}\bar{x}_{ij}} \tag{5}$$

- Computing the final crisp value

$$z_{ij} = \min_{j}\underline{\otimes}x_{ij} + y_{ij}\,\Delta_{min}^{max} \tag{6}$$

Step 3: the normalized direct crisp-relation matrix (*N*) is computed by equation (7).

$$N = \frac{1}{max\left(\max\limits_{1\le i\le n}\sum_{j=1}^{n}x_{ij}\,,\max\limits_{1\le j\le n}\sum_{i=1}^{n}x_{ij}\right)} \times Z \tag{7}$$

Step 4: the total-relation matrix (*M*) is constructed and calculated using equation (8), where I is the identity matrix.

$$M = N(I - N)^{-1} \tag{8}$$

Step 5: categorise the elements into net cause and net effect groups using (*R* – *C*), compute *R* and *C* using formulas (9) and (10), separately. The (*R* + *C*) vector, referred to as the “centrality” vector, indicates the relative importance of all elements. The elements in the (*R* – *C*) vector, known as the "cause-degree" vector, are categorised into the net cause group if $R_i - C_j > 0$, while those with $R_i - C_j < 0$ are placed in the net effect group.

$$R = \sum_{j=1}^{n} M_{ij} \forall i \tag{9}$$

$$C = \sum_{i=1}^{n} M_{ij} \forall j \tag{10}$$

Step 6: the ISM-MICMAC was implemented as outlined by Zhang et al. (2024). The parameter (λ) is calculated using equation (11) to filter out insignificant relationships and simplify the system structure, which is the addition formula of the mean values of M_{ij} and the standard deviation to the mean. This threshold setting is commonly adopted in ISM studies to improve the accuracy of the results of calculating the reachability matrix (Hu et al., 2024).

$$\lambda = \mu + \sigma \tag{11}$$

Step 7: the overall impact matrix (*O*) is constructed using equation (12), where I is the identity matrix.

$$O = M + I \tag{12}$$

Step 8: the overall impact matrix (*O*) is transformed into the reachability matrix (*G*) using equation (13).

$$G_{ij} = \begin{cases} 1, O_{ij} \ge \lambda \ (i,j = 1,2,\ldots,10) \\ 0, O_{ij} \ge \lambda \ (i,j = 1,2,\ldots,10) \end{cases} \tag{13}$$

Step 9: the multi-level hierarchical structure model is constructed using equation (14).

$$S_{(x_i)} = S_{(x_i)} \cap Q_{(x_i)} \tag{14}$$

It involves systematically decomposing the interrelationships among factors and revealing the internal hierarchy within the system. This procedure follows the principles of interval and inter-level decomposition, where system elements are first divided into distinct subsets and subsequently organised into hierarchical levels according to their relational dependencies. The process begins with the reachability matrix (*G*), which represents the direct and indirect relationships among factors derived from the previous analytical stage. For each factor x_i, two sets are identified: the reachability set $S_{(x_i)}$, which consists of all factors x_j for which $O_{ij} = 1$, representing those that can be reached from x_i; and the antecedent set $Q_{(x_i)}$, which consists of all factors x_j for which $O_{ji} = 1$, representing those that can reach x_i. The intersection of these two sets, $S_{(x_i)} \cap Q_{(x_i)}$, determines the hierarchical position of x_i. When the reachability set $S_{(x_i)}$ and its intersection are identical, that is $S_{(x_i)} = S_{(x_i)} \cap Q_{(x_i)}$, the factor x_i is assigned to the highest hierarchical level, as it no longer influences any other unassigned elements in the system. Once the factors at the highest level are identified, their corresponding rows and columns are removed from the reachability matrix (*G*). The same procedure is then repeated iteratively for the remaining factors until all elements are allocated to specific hierarchical levels.

Step 10: the driving power ($D_{(i)}$) and dependency value ($P_{(i)}$) of each factor are calculated using formulas (15) and (16), which is the sum the rows and columns of the reachability matrix (*O*), respectively. And then use the average value of dependence and driving power values as the dividing line of the quadrant and divide the factors into four quadrants: Autonomous (I), Independent (II), Linkage (III), and Dependent (IV).

$$D_{(i)} = \sum_{j=1}^{n} G_{ij} \tag{15}$$

$$P_{(i)} = \sum_{i=1}^{n} G_{ji} \tag{16}$$

3.3 Data Validation with Sensitivity Analysis

The results obtained from the data analysis with Grey-DEMATEL-ISM-MICMAC may be influenced by biases due to varying expertise and experience among the experts (Raj and Sah, 2019). To mitigate such effects and enhance the reliability and accuracy of the findings, sensitivity analysis was employed. Sensitivity analysis is a technique commonly used to examine how changes in a model's inputs influence the uncertainty in its outputs (Saltelli et al., 2008). This analysis involves adjusting the weight of the particular experts while maintaining uniform weights for the others to assess the overall effect on the system (Xia, Govindan and Zhu, 2015). This analytical framework finds extensive application in MCDA to ensure the robustness and reliability of the results (Więckowski and Sałabun, 2023).

The effects of these variations on the causal structure (Grey-DEMATEL), hierarchical levels (ISM), and driving-dependence classifications (MICMAC) were examined. By verifying that no single expert exerts disproportionate influence on the result, this validation step ensures the robustness of the analysis and strengthens the credibility of the findings.

4. Data Analysis and Result

4.1 Grey-DEMATEL Result

The Grey-DEMATEL technique was first applied to determine the causal relationships and influence strength among the identified critical success factors. The experts' judgments were aggregated to construct the initial Grey direct-relation matrix (*A*) using Grey system operations, as presented in Table 4, which was subsequently converted into crisp value through the CFCS method. The influence degree (*R*) and affect degree (*C*) were computed according to equations (3)-(10) to quantify the impact of each factor on others and vice versa.

Table 4: Grey direct-relation matrix (*A*)

	CSE	TE	PU	ATT	INT	SQ	INQ	PS	TS
CSE	[0.00, 0.00]	[0.60, 0.85]	[0.63, 0.88]	[0.52, 0.77]	[0.48, 0.73]	[0.31, 0.54]	[0.35, 0.60]	[0.29, 0.52]	[0.40, 0.63]
TE	[0.69, 0.94]	[0.00, 0.00]	[0.60, 0.85]	[0.58, 0.83]	[0.60, 0.85]	[0.40, 0.60]	[0.44, 0.65]	[0.29, 0.50]	[0.46, 0.67]
PU	[0.50, 0.75]	[0.56, 0.81]	[0.00, 0.00]	[0.65, 0.90]	[0.52, 0.77]	[0.40, 0.60]	[0.42, 0.65]	[0.38, 0.58]	[0.42, 0.63]
ATT	[0.54, 0.79]	[0.54, 0.79]	[0.60, 0.85]	[0.00, 0.00]	[0.58, 0.83]	[0.33, 0.54]	[0.35, 0.56]	[0.29, 0.52]	[0.31, 0.52]

	CSE	TE	PU	ATT	INT	SQ	INQ	PS	TS
INT	[0.46, 0.71]	[0.46, 0.71]	[0.50, 0.75]	[0.54, 0.79]	[0.00, 0.00]	[0.40, 0.60]	[0.52, 0.75]	[0.29, 0.50]	[0.40, 0.60]
SQ	[0.48, 0.71]	[0.58, 0.83]	[0.56, 0.81]	[0.56, 0.81]	[0.58, 0.83]	[0.00, 0.00]	[0.56, 0.79]	[0.44, 0.69]	[0.54, 0.79]
INQ	[0.40, 0.63]	[0.42, 0.64]	[0.56, 0.81]	[0.56, 0.81]	[0.48, 0.73]	[0.35, 0.58]	[0.00, 0.00]	[0.27, 0.50]	[0.29, 0.52]
PS	[0.44, 0.69]	[0.50, 0.75]	[0.54, 0.79]	[0.50, 0.75]	[0.46, 0.71]	[0.65, 0.90]	[0.48, 0.71]	[0.00, 0.00]	[0.69, 0.94]
TS	[0.58, 0.83]	[0.63, 0.88]	[0.56, 0.81]	[0.54, 0.79]	[0.52, 0.77]	[0.54, 0.77]	[0.48, 0.73]	[0.44, 0.69]	[0.00, 0.00]
CD	[0.54, 0.79]	[0.56, 0.81]	[0.65, 0.90]	[0.63, 0.88]	[0.67, 0.92]	[0.52, 0.75]	[0.54, 0.77]	[0.46, 0.71]	[0.54, 0.77]

As shown in Table 5, the factors with the highest influence degrees (*R*) include course design (CD), technical support (TS), and system quality (SQ), indicating that these elements exert substantial influence on other factors within the BL system. Conversely, the factors with the highest dependence degrees (*C*) include course design (CD), attitude (ATT), and interaction (INT), suggesting that these factors are most affected by others. Notably, CD exhibited both the highest influence and dependence values, highlighting its dual role as a central driver and recipient of systemic interactions.

Table 5: Grey-DEMATEL analysis result

	Influence Degree (*R*)	Affect Degree (*C*)	Centrality (*R* + *C*)	Cause-Degree (*R* - *C*)	Rank	Properties
CSE	7.67	8.42	16.09	-0.75	6	Effect
TE	8.43	8.74	17.16	-0.31	3	Effect
PU	8.08	9.31	17.39	-1.23	2	Effect
ATT	7.60	9.14	16.74	-1.54	4	Effect
INT	7.55	8.87	16.42	-1.33	5	Effect
SQ	8.73	7.00	15.73	1.73	8	Cause
INQ	7.01	7.46	14.47	-0.45	10	Effect
PS	8.70	5.92	14.62	2.78	9	Cause
TS	8.82	7.20	16.02	1.62	7	Cause
CD	9.04	9.57	18.60	-0.53	1	Effect

The causal degree (*R* – *C*) was further used to classify factor properties, identifying three causal factors and seven effect factors. The cause-effect relationships were visualised in Figure 2 to further clarify the connections. The factors above the horizontal axis, with a positive causal degree, represent causal drivers that exert a substantial influence on the system. In contrast, the factors below the axis, with a negative causal degree, are primarily affected by others. The centrality value (*R* + *C*) reflects the relative prominence of each factor, with higher scores indicating stronger systemic significance. The top three factors were course design (CD), perceived usefulness (PU), and technology experience (TE).

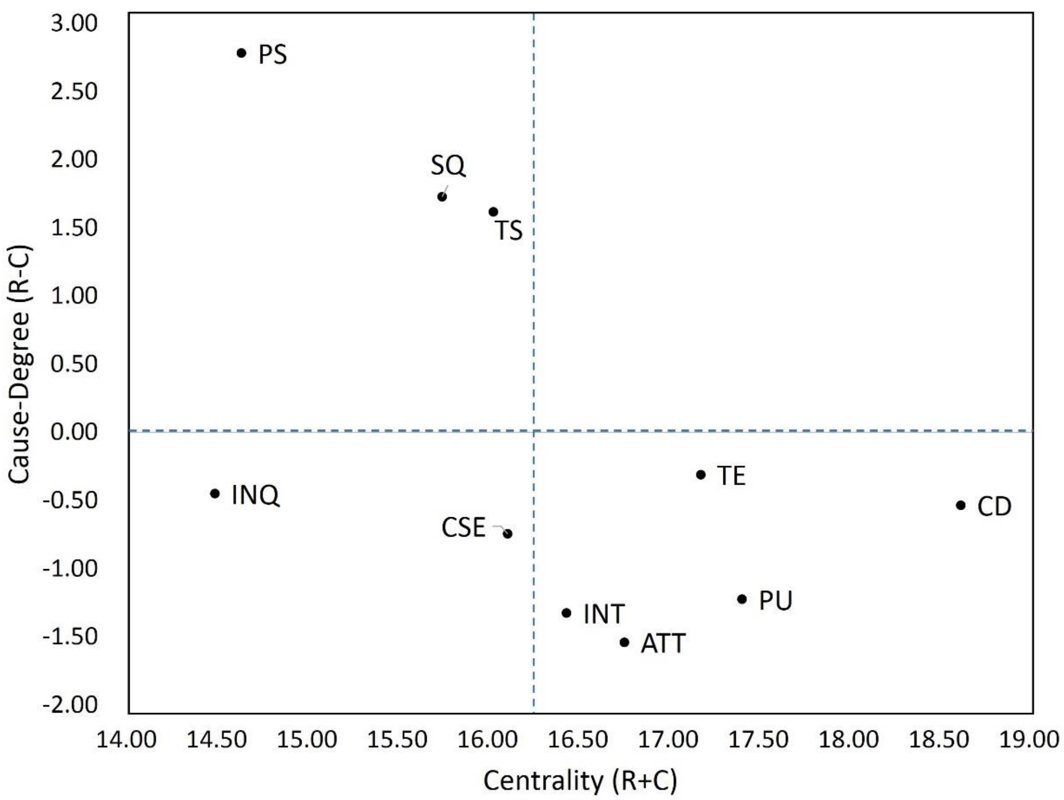

Figure 2: The cause-and-effect diagram

4.2 ISM Result

Based on the total-relation matrix (*M*) derived from Grey-DEMATEL, the ISM procedure was applied to construct a hierarchical structure of critical success factors. The reachability matrix (*G*) was constructed using equation (13) with the parameter (λ = 0.95) as outlined in Table 6.

Table 6: Reachability matrix (*G*)

	CSE	TE	PU	ATT	INT	SQ	INQ	PS	TS	CD
CSE	1	0	0	0	0	0	0	0	0	0
TE	0	1	1	1	0	0	0	0	0	1
PU	0	0	1	0	0	0	0	0	0	1
ATT	0	0	0	1	0	0	0	0	0	0
INT	0	0	0	0	1	0	0	0	0	0
SQ	0	0	1	1	1	1	0	0	0	1
INQ	0	0	0	0	0	0	1	0	0	0
PS	0	0	1	1	0	0	0	1	0	1
TS	0	1	1	1	1	0	0	0	1	1
CD	0	1	1	1	1	0	0	0	0	1

The reachability set ($S_{(x_i)}$) and antecedent set ($Q_{(x_i)}$) were derived for each factor through interval and inter-level decomposition, and intersections were used to determine factor levels iteratively. The factors whose reachability-antecedent intersection contained only themselves were classified at the top level, while remaining factors were processed as outlined in equation (14) until all were assigned to levels, as summarised in Table 7.

Table 7: The hierarchical set analysis

Factors	Reachability Set ($S_{(x_i)}$)	Antecedent Set ($Q_{(x_i)}$)	Intersection	Hierarchy
CSE	CSE	CSE	CSE	Top Layer
TE	TE, PU, ATT, CD	TE, TS, CD	TE, CD	Middle Layer
PU	PU, CD	TE, PU, SQ, PS, TS, CD	PU, CD	Top Layer
ATT	ATT	TE, ATT, SQ, PS, TS, CD	ATT	Top Layer
INT	INT	INT, SQ, TS, CD	INT	Top Layer
SQ	PU, ATT, INT, SQ, CD	SQ	SQ	Bottom Layer
INQ	INQ	INQ	INQ	Top Layer
PS	PU, ATT, PS, CD	PS	PS	Bottom Layer
TS	TE, PU, ATT, INT, TS, CD	TS	TS	Bottom Layer
CD	TE, PU, ATT, INT, CD	TE, PU, SQ, PS, TS, CD	TE, PU, CD	Middle Layer

The resulting multi-level hierarchical model organised the ten critical success factors into three distinct layers, as presented in Figure 3, which clearly illustrates the flow from root causes to intermediate factors and outcomes. The bottom layer represents the strategic level, comprising elements that exert long-term and structural influence on upper-level factors. These include system quality (SQ), policy support (PS), and technical support (TS). The middle layer bridges the strategic and outcome-oriented levels, including technology experience (TE) and course design (CD). The top layer encompasses the outcome-level factors, including computer self-efficacy (CSE), perceived usefulness (PU), attitude (ATT), interaction (INT), and information quality (INQ). This hierarchical structure provides clear insight into which factors serve as foundational strategic drivers and which are dependent outcomes, facilitating strategic prioritisation for BL initiative improvement.

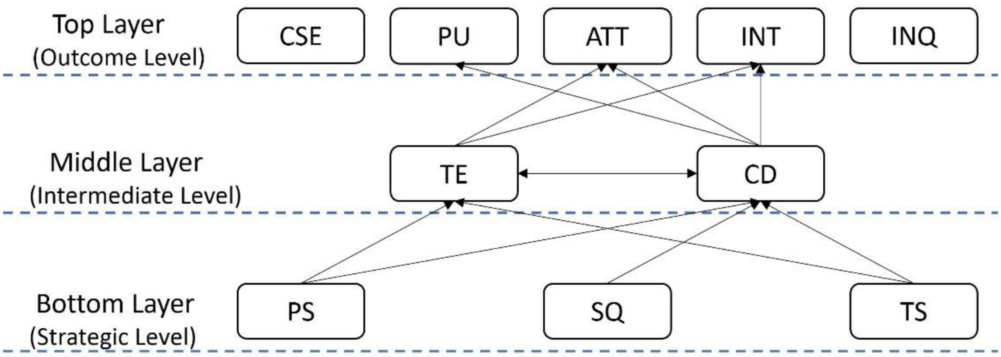

Figure 3: The multi-level structure diagram

4.3 MICMAC Result

MICMAC analysis was conducted to classify the BL critical success factors according to their driving power ($D_{(i)}$) and dependency value ($P_{(i)}$). Using the reachability matrix (*G*) from ISM, the $D_{(i)}$ and $P_{(i)}$ were calculated using equations (15) and (16), respectively, and the factors were subsequently categorised into four groups, as illustrated in Figure 4.

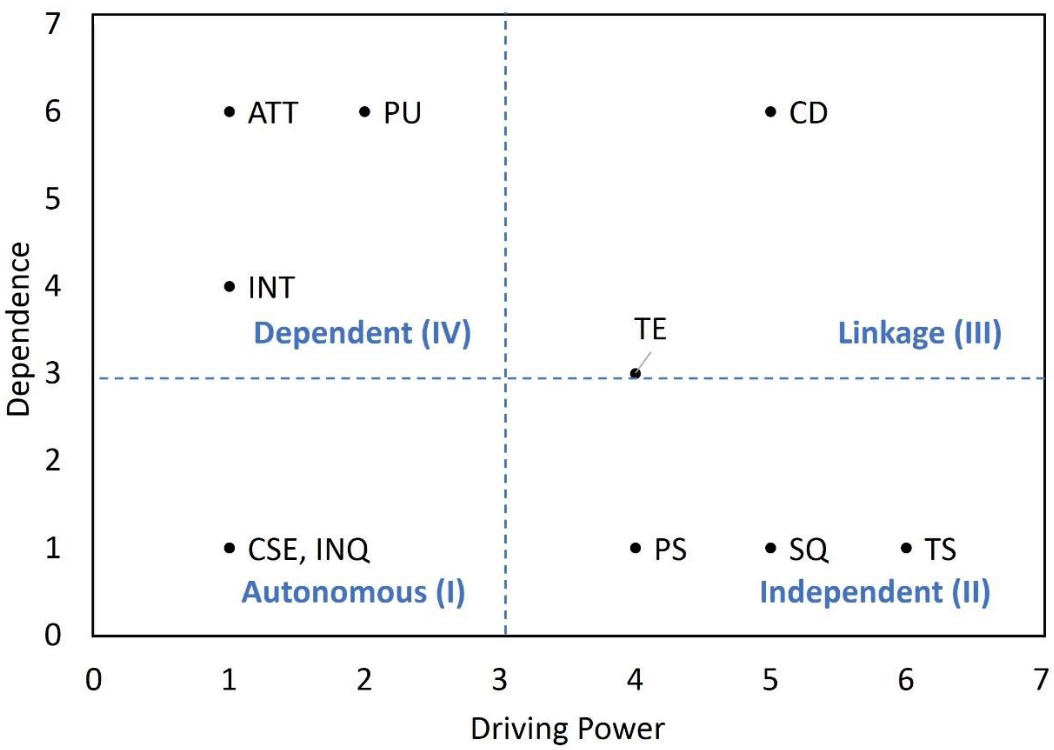

Figure 4: The multi-level structure diagram

The MICMAC analysis provides further insights into the driving and dependence relationships among critical success factors. Autonomous factors in quadrant I exhibit low driving and low dependence power, meaning they have little influence on other factors and are not significantly influenced by them. This group includes computer self-efficacy (CSE) and information quality (INQ), which tend to exert indirect or marginal effects on the outcome. Independent factors in quadrant II are characterised by strong driving power and weak dependence, exerting a strong influence on other factors in the system but are not heavily influenced by them. This quadrant includes policy support (PS), system quality (SQ), and technical support (TS), which are the factors that provide essential structural and operational support for BL practice. Linkage factors in quadrant III possess both high driving and dependence power, indicating that they both influence and are influenced by other factors in the system. They often act as crucial connectors between elements. This category comprises technology experience (TE) and course design (CD). Dependent factors in quadrant IV exhibit strong dependence but weak driving power. They are typically located in the upper layers of the ISM hierarchy, indicating that other factors greatly influence them but do not have a significant impact on the system. These include attitude (ATT), perceived usefulness (PU), and interaction (INT).

4.4 Sensitivity Analysis

Sensitivity analysis was performed to assess the robustness of the integrated Grey-DEMATEL-ISM-MICMAC results. The analysis compared the outcomes under different expert weighting schemes, where experts were categorised into four groups according to their teaching experience and domain expertise. By systematically varying the relative weights assigned to these groups, four experimental scenarios were developed, as summarised in Table 8.

Table 8: Different group weights assignment for sensitivity analysis

	Group 1	Group 2	Group 3	Group 4
Scenario 1	0.34	0.22	0.22	0.22
Scenario 2	0.22	0.34	0.22	0.22
Scenario 3	0.22	0.22	0.34	0.22
Scenario 4	0.22	0.22	0.22	0.34

For each scenario, the weighted aggregation of expert judgments was recalculated, and the corresponding causal relationships, hierarchical levels, and driving-dependence classifications were reanalysed, as presented in Table 9. The results demonstrated a high level of consistency across all scenarios, with no substantial differences observed in the causal structure, hierarchical layers, or factor classifications. This consistency suggests that experts with different levels of teaching experience and domain expertise share broadly similar perceptions towards the relationships of BL critical success factors. These findings confirm that the model's outcomes are structurally robust and are not significantly affected by variations in expert weighting schemes, thereby enhancing the credibility of the analytical results.

Table 9: Sensitivity analysis result

	DEMATEL (Cause-Effect)				ISM (Hierarchy Level)				MICMAC (Classification)			
	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4
CSE	-0.67	-0.82	-0.79	-0.82	Top	Top	Top	Top	I	I	I	I
TE	-0.36	-0.20	-0.35	-0.34	Middle	Middle	Middle	Middle	III	III	III	III
PU	-1.29	-1.13	-1.22	-1.19	Top	Top	Top	Top	IV	IV	IV	IV
ATT	-1.55	-1.44	-1.63	-1.48	Top	Top	Top	Top	IV	IV	IV	IV
INT	-1.43	-1.17	-1.61	-1.12	Top	Top	Top	Top	IV	IV	IV	IV
SQ	1.93	1.58	1.85	1.60	Bottom	Bottom	Bottom	Bottom	II	II	II	II
INQ	-0.68	-0.56	-0.43	-0.30	Top	Top	Top	Top	I	I	I	I
PS	2.84	2.72	2.91	2.63	Bottom	Bottom	Bottom	Bottom	II	II	II	II
TS	1.83	1.58	1.85	1.52	Bottom	Bottom	Bottom	Bottom	II	II	II	II
CD	-0.64	-0.55	-0.57	-0.50	Middle	Middle	Middle	Middle	III	III	III	III

5. Discussion

This study systematically analysed the cause-effect parameter, hierarchical structure, and driving-dependence mechanisms among BL critical success factors in HEIs using the integrated Grey-DEMATEL-ISM-MICMAC approach.

Cause-effect parameter: The Grey-DEMATEL results identified policy support (PS), system quality (SQ), and technical support (TS) as primary causal drivers that establish the institutional and technological conditions necessary for BL success. Among these, PS was identified as the most influential factor, offering institutional strategic direction for resource allocation and technological integration (Chen et al., 2024). The effective PS ensures the infrastructure development and platform stability, promotes user-centred design, and fosters collaboration among stakeholders (Laohajaratsang, 2017). SQ constitutes the second major causal driver by maintaining stable performance, intuitive interfaces, and convenient features of learning platforms (Katsarou, 2021), while efficient TS assists users in resolving technical difficulties, thereby minimising participation barriers and sustaining online learning activities (Feng, He and Ding, 2023). These success factors collectively establish a supportive environment that enables pedagogical and technological advancements. Notably, course design (CD) exhibited the highest level of centrality in the causal structure, indicating its strong interconnectedness with other factors in the system (Wang et al., 2025). This implies that HEIs should place greater emphasis on ensuring coherent alignment among course content, instructional strategies, and technological features to strengthen the interaction and enhance cognitive engagement (Law, Geng and Li, 2019).

Hierarchical structure: The ISM analysis revealed a distinct three-layer hierarchy that aligns closely with the causal findings. The foundational layer comprises policy support (PS), system quality (SQ), and technical support (TS), forming the structural base of the BL system. Technology experience (TE) and course design (CD) constitute the intermediate layer, representing the mechanisms that transform institutional and technological resources into pedagogical processes. This finding is consistent with the results of the DEMATEL analysis, where CD exhibited the highest values of both influence and dependence. A well-designed BL course not only shapes learners' perceptions and experiences at the outcome level but is also influenced by enabling factors at the strategic level. This suggests that prioritising course design capacity within BL development strategies is essential to ensure that institutional and technological resources are effectively integrated into pedagogical practice, ultimately leading to improved learning performance. The top layer comprises outcome-oriented elements, including perceived usefulness (PU), attitude (ATT), and interaction (INT), which reflect the learners' behavioural and cognitive responses. This multi-layered structure illustrates a logical progression from institutional and technological support to individual-level engagement and perception. This finding is consistent with prior studies (Arjanto and Telussa, 2024), which indicate that socio-economic support and the provision of adequate technological infrastructure enhance the quality of pedagogical design, thereby improving student participation, engagement, and learning outcomes. Interestingly, computer self-efficacy (CSE) and information quality (INQ) appear relatively independent within the hierarchical model, revealing that they have a limited influence within the current system structure. In other words, these two variables exhibit relatively weak causal connections with other factors in the BL system: they are neither strongly influenced by foundational institutional support nor directly associated with students' behavioural and cognitive responses at the outcome level. This suggests that their influence may operate more indirectly through pedagogical mechanisms or other intermediary elements. Moreover, the bidirectional relationship between CD and TE suggests the presence of a self-reinforcing mechanism within the BL process. In other words, these factors mutually shape and reinforce one another. This observation aligns with the findings of Konstantinidou and Nisiforou (2022), who argued that well-structured and logically sequenced course design promotes higher technological engagement and improved learning outcomes. These technological improvements subsequently feed back into the instructional process, contributing to higher-quality design practices.

Driving-dependence classification: The MICMAC analysis further substantiates the structural interpretation by categorising factors according to their driving and dependence power. Through this classification, the analysis clarifies their functional roles within the causal network and helps to establish strategic intervention priorities (Javan Jafari Bojnordi et al., 2025). PS, SQ, and TS are categorised as independent factors, serving as fundamental strategic levers for achieving BL success. This result is consistent with the patterns identified in the Grey-DEMATEL and ISM analyses, underscoring the necessity for HEIs to strategically invest in these high-driving elements to ensure the sustainable advancement of BL initiatives. Without adequate investment in those enabling conditions, technology-enhanced learning environments are unlikely to achieve sustained effectiveness. TE and CD act as linkage factors, connecting institutional inputs and learning outcomes. This implies that they serve as key transformative mechanisms through which institutional investments are converted into meaningful learning experiences. This helps explain why many HEIs experience limited success in implementing BL initiatives (Sareen and Mandal, 2024): even when supportive policies, technical support mechanisms, and stable systems are well-provided, BL practices are often implemented as a simple juxtaposition of face-to-face instruction and online components (Rasheed, Kamsin and Abdullah, 2020; Rix, 2011), leading to constrained learning experiences. This finding indicates that the instructional effectiveness of BL courses depends on instructors' capacity to reconfigure the online and offline instructional structures in line with system capabilities and level of technical readiness (Ren et al., 2025). Consequently, providing targeted professional development for instructors in BL design and technological competencies plays a substantial role in supporting instructional effectiveness, and ultimately, improving students' learning experiences. For the administrators and policymakers of HEIs, fostering cross-functional collaboration among educators, instructional designers, and technologists is essential for aligning pedagogical objectives with technological capabilities to maximise the success of the BL initiatives. Conversely, ATT, PU, and INT are identified as dependent factors, reflecting how upstream elements collectively shape user experiences and learning results. These variables serve as evaluation indicators for monitoring the effectiveness of BL, enabling HEIs to iteratively refine their policies and strategic orientations through continuous assessment. Overall, this classification clarifies a coherent strategic framework that independent factors constitute the principal targets for institutional investment, linkage factors function as systemic connectors that transform the organisational investments into learning effectiveness, dependent factors act as outcome-based monitoring indicators, and autonomous factors occupy marginal positions within the system. These findings complement previous BL research (Hua, Wang and Li, 2024; Jannat Nipa and Hoque, 2025) that has applied linear analytical approaches to examine predictive relationships among variables, primarily focusing on what factors matter and the strength of their effects on learning outcomes. In contrast, this study moves beyond a linear causal perspective by demonstrating how these factors interact within the system to influence BL performance. This structured perspective enables HEIs to avoid fragmented improvement strategies and supports the BL progression toward more systematic and sustainable development.

By synthesising the three analytical results, this study conceptualises BL as a dynamic system shaped by multi-level interactions among institutional policies, technological affordances, and pedagogical practices. The findings provide practical implications and actionable insights for higher education administrators and policymakers seeking to enhance the effective management and sustainability of BL initiatives. By leveraging the identified causal and hierarchical structures, decision-makers can more effectively prioritise key areas for improvement. In particular, the institutional and technological dimensions should be recognized as the structural basis of the

BL system and serve as the foundational starting points for systemic optimisation; whereas course design and technology experience act as key leverage points for continuous enhancement. These mediating mechanisms transform institutional and technological drivers into pedagogical effectiveness. These findings also suggest that achieving efficiency, resilience, and long-term sustainability of BL systems in post-pandemic e-learning development requires strategic investment in these high-driving-power factors, as well as a systematic approach that aligns institutional governance, digital infrastructure, and pedagogical practice. In practical terms, HEIs should establish clear institutional guidelines and governance frameworks for the implementation of BL initiatives, ensuring that institutional support mechanisms, digital infrastructure, and technical resources are systematically aligned with course development needs. Institutions should also communicate these policies effectively to faculty and provide sustained technical and instructional support to facilitate the design and delivery of high-quality BL courses. Furthermore, improving system quality and ensuring responsive technical support are essential for maintaining reliable and user-friendly learning environments that empower instructors to design interactive and engaging learning experiences

This study contributes to the literature by introducing a systems science-based analytical framework into educational research, integrating causal, hierarchical, and driving-dependence analyses. This systemic perspective moves beyond factor-based explanations toward a structural understanding of BL success. The integrative approach advances the understanding of how individual, technological, environmental, and course dimensions interact to support BL success, offering a systematic foundation for evidence-based educational strategy prioritisation and policymaking in HEIs.

6. Conclusion

This study employed the integrated Grey-DEMATEL-ISM-MICMAC approach to systematically model the causal interdependencies, hierarchical structure, and driving-dependence classification of BL critical success factors in HEIs. The integrated analysis visualised how these factors interact within the BL system, offering a holistic understanding of their structural and functional relationships. The results identified policy support, system quality, and technical support as key causal drivers that form the structural foundation of the BL system and act as independent factors with strong driving power in achieving BL success. Course design functions as the pivotal mediator linking institutional enablers and learner outcomes, characterized by the highest centrality within the BL system. While attitude, perceived usefulness, and interaction were classified as dependent factors, representing the ultimate manifestations of system performance. These findings also indicate that well-established institutional and technological drivers do not, in themselves, guarantee positive learning experiences. In practice, the gap often arises at the level of instructional implementation, where course design shapes whether institutional investments transform into meaningful interaction, perceived value, and positive learning attitudes. These structured relationships collectively form a self-reinforcing feedback mechanism, wherein institutional policies, technical support, and system functions enable high-quality course design, which subsequently enhance learners' perceptions, engagement, and attitudes. This cyclical mechanism continuously drives improvement and innovation in BL environments.

The findings provide data-driven insights for HEI policymakers and educators, emphasizing the need to strategically allocate resources towards those strategic leverage points for optimising BL successful implementation. Specifically, institutions should prioritise institutional policy alignment, high-quality system infrastructure, strong technical support, and task-technology alignment in course design as strategic enablers that enhance learning engagement and effectiveness, ensuring the long-term sustainability of BL implementation in HEIs.

This study has several limitations that should be acknowledged. First, the participating experts were drawn from a single HEI, which may limit the generalisability of the findings, as the results may partly reflect contextual characteristics specific to this institutional environment. Second, the analysis relied primarily on expert judgement rather than large-scale empirical data. Although expert-based evaluations are widely used in systems-oriented approaches to identify structural relationships among factors, further empirical validation would strengthen the robustness of the findings. Future research could therefore extend this work through cross-cultural comparative studies to examine whether the identified causal relationships and hierarchical structures vary across different higher education contexts. In addition, longitudinal studies could further refine understanding of the dynamic interplay among BL success factors as these relationships evolve over time with institutions' growing experience in BL implementation and digital infrastructure development within technology-mediated learning environments.

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AI Statement: ChatGPT was used solely to improve language clarity and translation. All study design, analysis, and conclusions were conducted independently by the researchers.

Ethics Statement: All participation was voluntary, with informed consent obtained prior to the survey. The study complied with the Declaration of Helsinki and was approved by the Chiang Mai University Ethics Committee (COA No. 158-67).

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